Advances in Decision Support Systems for Risk and Return Management in Complex Networks

Kumulative Dissertation

der Wirtschaftswissenschaftlichen Fakultät

der Universität Augsburg

zur Erlangung des Grades eines

Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

vorgelegt

von

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(Master of Science)

Augsburg, Oktober 2018

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Datum der mündlichen Prüfung:	12.12.2018

“A ship is safe in harbor, but that's not what ships are for.”

William Greenough Thayer Shedd

American Theologian (1820 - 1894)

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Index of Research Papers

This doctoral thesis contains the following research papers:

Research Paper 1 (RP 1):

Berger S, Häckel B, Häfner L (2019) Organizing Self-Organizing Systems: A Terminology, Taxonomy, and Reference Model for Cyber-Physical Production Systems.

In: *Information Systems Frontiers, 1-24.* (online)

https://link.springer.com/article/10.1007/s10796-019-09952-8

VHB-JOURQUAL 3: category B

Research Paper 2 (RP 2):

Häfner L, Keller R, Sachs T, Fridgen G (2020) Scheduling Flexible Demand in Cloud Computing Spot Markets - A Real Options Approach

In: *Business & Information Systems Engineering, 62(1), 25-39*

VHB-JOURQUAL 3: category B

Research Paper 3 (RP 3):

Häckel B, Häfner L, Übelhör J (2020) Toward Strategic Decision Support Systems for Systemic Risk Management.

Working Paper

Research Paper 4 (RP 4):

Fridgen G, Häfner L, König C, Sachs T (2016) Providing Utility to Utilities: The Value of Information Systems Enabled Flexibility in Electricity Consumption.

In: *Journal of the Association for Information Systems, 17(8), 537-563*

VHB-JOURQUAL 3: category A

Research Paper 5 (RP 5):

Drasch B, Fridgen G, Häfner L (2020) Decision Support in Building Automation - A Data-driven Demand Response Approach for Air Conditioning Systems.

Working Paper

Research Paper 6 (RP 6):

Häfner L (2018) Entscheidungsunterstützungssysteme für die flexible Beschaffung von Energie unter integrierten Chancen- und Risikoaspekten.

In: *HMD - Praxis der Wirtschaftsinformatik, 55(3), 627-645*

VHB-JOURQUAL 3: category D

Research Paper 7 (RP 7):

Unterberger E, Buhl HU, Häfner L, Keller R, Ober S, Paulick-Thiel C, Reinhart G, Schöpf M, Simon P (2018) The Regional and Social Impact of Energy Flexible Factories.

In: *Procedia Manufacturing, 21, 468-475*

VHB-JOURQUAL 3: unranked

I Introduction

Digital transformation in the business sector

With the onset of the digital age, a growing number of human beings obtains easier access to a tremendously growing amount of information. Gathering and processing information is enabled by *information and communication technology* (ICT), which is rapidly developing, interconnecting, and influencing human life (Bojanova 2015). In spite of many believers, digitalization is not a new phenomenon, since ICT already replaced many jobs, especially of unskilled and manual workers (Van Reenen 2011), and led to the establishment of the internet as a global communication platform (Legner et al. 2017) a few decades ago. However, current ICT, which is summarized under the term *SMAC* (social media, mobility, analytics, and cloud computing), triggers a new and unprecedented wave of digitalization and plays an increasingly important role in the business sector, the non-profit (social) sector, and the private sector (Raman 2016; Legner et al. 2017). Increasingly embedded and connected SMAC form the *internet of things* (IoT), which is a “dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual ‘things’ have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network" (IERC 2018). According to estimations of Gartner (2017a), the number of “things” connected in the IoT will rise to 20.4 billion by 2020 (6.38 billion by 2016). Moreover, the potential economic impact of IoT applications is estimated to reach $11.1 trillion per year by 2025 ($0.9 trillion per year by 2015) (McKinsey 2015).

In the business sector, increasing data volumes, ICT, and IoT are going to become major drivers of innovation and transformation, with plenty of opportunities and challenges (Kagermann 2015). Thereby, digital transformation is defined as “changes in ways of working, roles, and business offering caused by adoption of digital technologies in an organization, or in the operation environment of the organization” (Parviainen et al. 2017, p. 64). To remain or enhance their competitive position, companies are forced to leverage data and new ICT to increase efficiency and flexibility of their production, supply chain, and internal processes and to develop new business models (Kagermann 2015). Thereby, major success factors for companies are that they manage (i) to focus on the right data and ICT, which fit their existing business models or open up new promising ones, (ii) to leverage these data and ICT faster than their competitors, (iii) to align digital transformation with customer needs and a customer-centric perspective, and (iv) to transform not only technology but also organizational processes, people's skills, and culture (Earley 2014; Biahmou et al. 2016).

The development of digitized value networks

In the production environment, digital transformation is characterized by "highly flexible control of production and associated areas via *Cyber-Physical Systems* that are networked in real time and are now replacing centrally controlled Computer-Integrated Manufacturing" (Kagermann 2015, p. 32). As the term *Cyber-Physical System* does not particularly refer to production environments but to systems that integrate computational and physical capabilities in general (Baheti and Gill 2011), this doctoral thesis follows Penas et al. (2017) and introduces the term *Cyber-Physical Production System* (CPPS) that describes "systems that synergize conventional production technology and IT, which allow machines and products to communicate with each other in the IoT environment" (Penas et al. 2017, p. 55). CPPSs can "flexibly adapt to varying demands, changing customer requirements, and breakdowns of production facilities during the runtime of the production processes" (Vogel-Heuser et al. 2014, p. 714). Their adaptability by means of easier (IT-based) integration is called *plug-and-produce* (Jeschke et al. 2016). Therefore, CPPSs help to make small batch sizes and mass customization economically profitable. CPPSs are an enabler for IoT in value networks: First, they integrate (vertically) business, production processes, and ICT at different hierarchical levels. Second, they integrate (horizontally) production processes and ICT in different stages of the value network both within a company and across several companies (Liu et al. 2015; Pérez et al. 2015). In the following, this doctoral thesis applies the term *digitized value networks* to refer to value networks that leverage the use of inter-organizational ICT and horizontally integrated CPPSs.

In digitized value networks, CPPSs cooperate across company borders to form complex, distributed, and autonomous ecosystems, whereby increased collaboration between companies is an enabler for jointly developing and applying new digital business models and hybrid value creation (Martín-Peña et al. 2018). Companies that participate in digitized value networks may further profit from increased collaboration productivity and therefore lower production costs (Schuh et al. 2014). Thereby, competition will not be limited to individual companies but involve the whole digitized value network (Kagermann 2015). Although the transition toward digitized value networks is expected to be an evolutionary (rather than a revolutionary) process (Kagermann 2013), many companies require substantial investments in digital technologies to remain competitive (De Carolis et al. 2017). In particular, most companies regard this necessity for substantial investments as one of the greatest challenges in industrial digitalization (Jäger et al. 2016).

Challenges for industries due to global energy transition

High adaptability and flexibility of CPPSs and digitized value networks open new opportunities not only for customer-centric production control but also for optimization of production costs. Especially energy costs become an increasingly important competitive factor as retail prices have increased in many countries for several years (Ecofys 2016; European Commission 2014; Dombrowski and Riechel 2013). Depending on country and industry sector, energy costs already amount to a significant share of total production costs. A study on European industries for the years 2008 to 2013 shows that energy costs are usually between 3% and 10% of total production costs (Ecofys 2016). Energy costs could further increase in future, inter alia, because of the world's energy demand, which is projected to increase by 28% between 2015 and 2040, especially due to increased economic growth, access to marketed energy, and quickly growing populations in non-OECD countries that outweigh savings due to increasingly energy efficient technologies (U.S. Energy Information Administration 2017). Thereby, the industrial sector is the world's largest energy-consuming sector being accountable for 55% of the world's total energy demand (U.S. Energy Information Administration 2017). Furthermore, industrial sector's energy demand is expected to increase by 18% between 2015 and 2040 (U.S. Energy Information Administration 2017). Despite some regulatory failures in the past, there is a growing political effort to create regulation and incentives that favor sustainable use of energy (Gillingham and Palmer 2014; Rammer et al. 2016; Taggart 2016). In particular, there is a worldwide political endeavor and competition to create sustainable energy systems (World Economic Forum 2017), which especially affects the industrial sector. This endeavor stems from many countries' objective to stop global warming. At the UN Climate Change Conference in 2015, participants agreed to hold "the increase in the global average temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change" (United Nations 2015, p. 21). Therefore, many countries started to deconstruct coal-fired power stations and to invest in the establishment of a sustainable energy production, especially based on wind turbines and photovoltaic systems, which are nowadays the world's fastest-growing energy source (U.S. Energy Information Administration 2017; World Economic Forum 2017). The greatest risk for this energy transition is the uncontrollable availability and weak predictability of solar radiation and wind that threatens the balance between energy supply and demand, especially for electricity (Child et al. 2017; Kommalapati et al. 2017; Ibrahim et al. 2011). Furthermore, a large share of wind turbines and photovoltaic systems on total electricity production tends to increase electricity price volatility (Wozabal et al. 2016). Thereby, security of electricity supply and electricity price stability are major challenges for politics, economics, and society (BMWi 2016).

Energy flexibility in digitized value networks

Hence, companies that pay electricity tariffs based on market prices should consider their timing for purchasing and consuming electricity. Thereby, *demand response* (DR) defines "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time […]" (Federal Energy Regulatory Commission 2008, p. C-2). Three approaches to conduct DR exist: First, companies may exploit their temporal flexibility by scheduling production processes with the objective to avoid electricity price peaks (Unterberger et al. 2017) or to offer flexible loads on balancing markets. In this context, Graßl et al. (2013) define energy flexible manufacturing as "the ability of a production system to adapt itself fast and without remarkable costs to changes in energy markets" (p. 303). Second, companies may recourse to battery storages or *power-to-x* (P2X) technologies that (temporarily) transfer electricity in other energy carriers such as hydrogen and heat (Zöphel et al. 2018). During peaks on electricity or balancing markets, they may use these energy carriers (reversely) to produce electricity. Third, they may recourse to their own energy generation (e.g., combined heat and power plants). Companies can apply all three DR approaches solely or as convex combination to utilize temporal flexibility. Thereby, they may consider additional investments, e.g., for acquiring the respective DR technology or for ICT that enables the automated identification and exploitation of savings potentials due to energy flexibility measures. Moreover, as the deferral of electricity consumption might cause additional opportunity costs, companies should include these costs within business case calculations. In the following, this doctoral thesis applies the term *energy flexibility management* to refer to an industrial company's decision-making on how to invest in DR and when to use DR in daily business. More precisely, energy flexibility management in this thesis is limited to subactivities in digitized value networks. Other application areas for energy flexibility management such as private households or utility companies are excluded.

Deciding on investments in digitized value networks and energy flexibility management

With the objective to guide manufacturing companies investing in digital transformation, De Carolis et al. (2017) suggest a four-step framework: First, the *maturity assessment*, in which companies should identify their digital maturity and capabilities in further digitizing their processes. Second, the *analysis of strength and weaknesses* in each process. Third, the *opportunity identification*, which discovers an investment's potential benefits. Fourth, *the digital transformation roadmap definition*, to prioritize feasible investments according to their expected benefits. At first glance, this framework's suggestion to derive the status quo, investment objectives, and a roadmap to meet these objectives seems intuitive. However, there is a major drawback: De Carolis et al. (2017) limit their framework to the analysis of opportunities, not considering risks. A common paradigm for decision-making (such as investment decisions) is *value-based management* (VBM). VBM extends the shareholder value approach and demands that all business activities must follow the objective to maximize a company's fundamental value (Coenenberg and Salfeld 2007). Thereby, a long-term perspective of investments is necessary, as long-term productivity enables both sustainable competitive advantages and increasing shareholder value (Rappaport 1992). Moreover, decision-making complying with VBM must integrate both risk and return measures when considering value contributions (Buhl et al. 2011). This especially applies for investments in digitized value networks and related energy flexibility management. The intensive integration of CPPSs in digitized value networks yields complex interrelations and interdependencies between flows of material, information, and energy and, therefore, causal chains between companies that need to be considered (Lasi et al. 2014; Sassanelli et al. 2018; Broy et al. 2012; Unterberger et al. 2017). Thereby, CPPS as advanced production systems require "high capital expenditure along with high investment risk" (be Isa et al. 2018, p. 490). Especially ICT requires irreversible investments, which are often subject to high uncertainty regarding the meeting of technical requirements and economical objectives (Lee and Lee 2015). This also affects energy flexibility management: Since the energy system and energy markets exhibit an unprecedented increase in complexity, companies that strive to apply DR approaches require massive ICT investments to manage these complexities and enable energy flexibility measures (Kagermann 2015, Unterberger et al. 2017, Schott et al. 2018). Moreover, successful investments require sufficient experience and knowledge to choose appropriate technology (Wiesner et al. 2018), which is another potential source for investment risks.

To sum up, this doctoral thesis emphasizes the need to follow principles of VBM using an integrated risk and return perspective when deciding on investments in digitized value networks and related energy flexibility management. Following Hertel (2015), the *integrated risk and return management cycle* is an enhancement of the traditional risk management cycle that "specifies a uniform pattern that enables the systematic management of investments by outlining a structured process" (p. 2). Figure I-1 illustrates this cycle.

Figure I-1: Integrated risk and return management cycle (Hertel 2015)

In literature, many alternative risk (and return) management approaches exist that vary in number (between three and seven), labeling and description of steps, although they commonly emphasize a (never-ending) cycling system (Kallman and Maric 2004). As all these approaches exhibit comparable elements (Kallman and Maric 2004), this doctoral thesis continues with the four-step cycle, which is an appropriate granularity to classify included research papers (cf. Section I.2).

- *Identification*: The first step to analyze investments in digitized value networks and related energy flexibility management is risk and return identification. Thereby, opportunities and threats of different investment alternatives (including the option to not invest) may occur within the company or at the interface to other companies and should be collected and classified along with respective interdependencies. Due to the development toward digitized value networks, investment alternatives are increasingly located at the interface to other companies (Sassanelli et al. 2018).

- *Quantification*: In the second step, investment alternatives should be evaluated according to their estimated long-term value contributions (in terms of cashflows) to the company. To consider investment risks and returns, decision-makers require scenario analysis and volatility measures based on cashflow distributions rather than point estimators. Thereby, decision-makers should explicitly consider managerial flexibility of actions to not underestimate an investment alternative's value (Trigeorgis 1996). Moreover, they should consider interdependencies between different projects' cashflows, diversification effects, and non-monetary factors such as an organization's maturity (or readiness) for investments (De Carolis et al. 2017).
- *Control*: In the third step, decision-makers should use previous risk and return quantification to decide on investments alternatives. Thereby, they could execute all investments that yield (from a risk-adjusted point of view) positive value contribution to the company, or, if budgets are limited, prioritize the most promising ones.
- *Monitoring and Reporting*: In the last step, the chosen projects should be continuously monitored to be able to react to changing circumstances and frame conditions (e.g., to adjust a project's scope if requirements change). Therefore, further loops of the integrated risk and return management cycle could be advantageous. By monitoring projects, decision-makers might learn from previous failures to improve future investment decision making. Moreover, decision-makers might be obligated to report a project's progression to internal and external stakeholders (e.g., management or supervisory bodies).

Decision support systems and purpose of this thesis

As mentioned above, deciding on investments in complex and interdependent digitized value networks and related energy flexibility management is a challenging task. Therefore, decision-makers would benefit from the development of *decision support systems* (DSSs), i.e., ICT that "can be used to support complex decision making and problem-solving" (Shim et al. 2002, p.111). DSSs can help "to set strategic technological priorities and formulate IT and R&D investment strategies" (Skulimowski 2011, p. 13). Thereby, DSSs are auxiliary systems, which do not intend to substitute human decision-making (Power 2002). DSSs are usually highly specialized, i.e., they are designed in a way that they assist decision-making by applying specific expertise (Bonczek 2014). This expertise should comprise "(1) knowledge of symptoms and indicators related to a particular topic or domain; (2) understanding of the relations among symptoms and of problems and solutions within that domain; and (3) ‘skill’ or methods for solving some of the problems” (Power 2002, p. 142). Thereby, designers of DSSs must guarantee that such ICT actually improves decision-making (Zhang et al. 2015).

Against this background, the research work carried out in this doctoral thesis contributes to the design and development of new DSSs that assist investment risk and return management in (i) digitized value networks and (ii) related energy flexibility management considering principles of VBM. The following Section I.1 illustrates the objectives and structure of this thesis. In the subsequent Section I.2, the corresponding research papers are embedded in the research context and the fundamental research questions are highlighted.

I.1 Objectives and Structure of this Thesis

The main objective of this doctoral thesis is to contribute to investment risk and return management in digitized value networks and related energy flexibility management. Thereby, this doctoral thesis identifies and addresses important research questions, which support the design and development of future investment DSSs that follow principles of VBM. Table I.1-1 gives an overview of the pursued objectives and structure of this doctoral thesis.

I Introduction	
Objective I.1:	Outlining the motivation, objectives, and the structure of this doctoral thesis
Objective I.2:	Embedding the included research papers into the context of this doctoral thesis and formulating fundamental research questions
II Decision Support for Risk and Return Management in Digitized Value Networks	
Objective II.1:	Enabling the development of future CPPS modeling approaches by providing a terminology, taxonomy, and reference model for CPPS entities
Objective II.2:	Reducing companies' costs for external cloud computing services by evaluating and exploiting temporal consumption flexibility using a real options approach
Objective II.3:	Improving systemic risk management in digitized value networks by providing a functional design and generic system architecture for DSSs that identify, evaluate, control, and monitor systemic risks
III Decision Support for Risk and Return Management in Energy Flexibility Management	
Reducing industrial companies' electricity costs while improving utilization of renewable energy sources by…	
Objective III.1:	… evaluating and utilizing short-term temporal flexibility in electricity consumption using a real options approach
Objective III.2:	… optimizing real estate air conditioning systems based on expected electricity price and demand development
Objective III.3:	… providing functional requirements and a generic system architecture for DSSs that enable an ICT-based energy flexibility management
Objective III.4:	… utilizing industrial energy flexibility under consideration of technological, ecological, and social restrictions using a transdisciplinary research approach
IV Results and Future Research	
Objective IV.1:	Presenting the key findings of this thesis
Objective IV.2:	Identifying and highlighting areas for future research

Table I.1-1: Objectives and structure of the doctoral thesis

I.2 Research Context and Research Questions

In the following section, research papers included in this doctoral thesis are embedded in the research context and their research questions are motivated with respect to the above stated objectives. As this doctoral thesis aims to contribute to investment risk and return management, research papers are classified within the integrated risk and return management cycle (cf. Figure I.2-1), although, for dramaturgical reasons, the doctoral thesis is structured along the two applications areas of digitized value networks and therein included energy flexibility management.

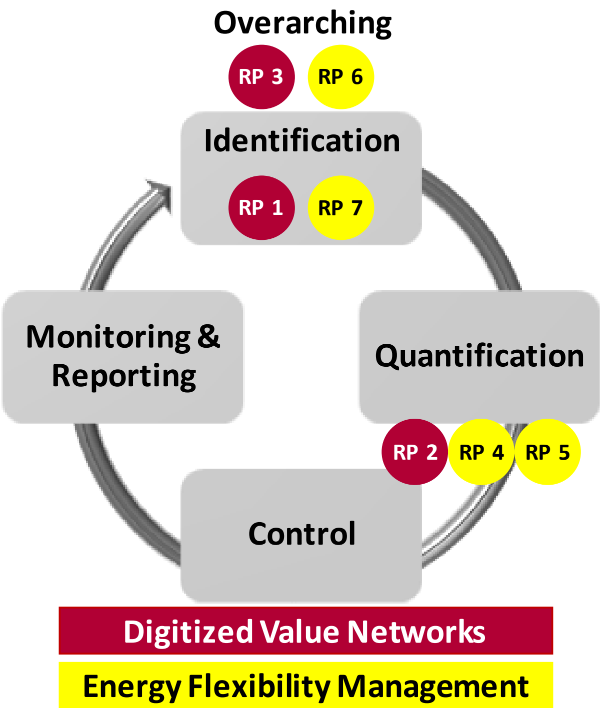

Figure I.2-1: Research papers embedded in the integrated risk and return management cycle

In the context of digitized value networks (Section II), *Research Paper* (RP) 1 starts on a rather fine-grained level by researching CPPSs. More precisely, the development of future CPPS modeling approaches is enabled by RP 1's definition and classification of CPPS entities and analysis of their relations, which also improves investment risk and return identification in digitized value networks. RP 2 helps companies to reduce their costs for services on cloud computing spot markets by evaluating and exploiting temporal flexibility using a real options approach. As this simultaneously supports quantifying and deciding on respective investments, this paper contributes to investment risk and return management. RP 3 contributes to systemic risk management in digitized value networks by providing a functional design and generic system architecture for respective DSSs. As an ICT-supported systemic risk management helps to identify, evaluate, decide on, and monitor respective investments (e.g., countermeasures against systemic risks), this paper addresses all four steps of the cycle in an overarching manner. In the context of decision support for investment risk and return management in energy flexibility management (Section III), all four research papers follow the objective of reducing companies' electricity costs by utilizing temporal consumption flexibility in the light of volatile spot market prices. Since spot market prices also reflect current availability of renewable energy sources (i.e., increasing supply of solar and wind power reduces spot market prices), these papers simultaneously contribute to a sustainable energy consumption. Thereby, RP 4 and RP 5 provide DR approaches for evaluating and exploiting temporal flexibility in electricity consumption in general (RP 4) and for the special use case of building air conditioning systems (RP 5). Regarding investment risk and return management, both papers contribute to risk and return quantification and control. RP 6 provides functional requirements and a generic system architecture for DSSs that assist companies in energy flexibility management. Thereby, all four steps of the cycle are included in an overarching manner. Finally, RP 7 contributes to investment risk and return identification as a transdisciplinary research approach for utilizing industrial energy flexibility is provided that explicitly considers technological, ecological, and social restrictions.

I.2.1 Section II: Decision Support for Risk and Return Management in Digitized Value Networks

Research Paper 1 (RP 1)*: "Organizing Self-Organizing Systems: A Terminology, Taxonomy, and Reference Model for Cyber-Physical Production Systems"*

Research Paper 2 (RP 2)*: "Scheduling Flexible Demand in Cloud Computing Spot Markets - A Real Options Approach"*

Research Paper 3 (RP 3): *"Toward Strategic Decision Support Systems for Systemic Risk Management"*

The digital transformation of conventional production systems to CPPSs and interconnected digitized value networks poses many opportunities, but also challenges for companies. On the one hand, CPPSs enable autonomous production management, resource efficiency, shorter time-to-market, flexible adaption of production processes to varying customer demand, and mass customization of products (Lasi et al. 2014; Tjahjono et al. 2017). On the other hand, progressing integration of ICT in CPPSs increases manufacturing complexity in digitized value networks (Kagermann 2013). Therefore, “models that describe the structure, communication interfaces, and capabilities of the different entities inside a CPPS and the functionalities of the production facilities and their components and the specification of products are required” (Vogel-Heuser et al. 2014, p. 714). “Modelling can act as an enabler for managing this growing [CPPS] complexity” (Kagermann 2013, p. 42). Managing CPPSs complexity and creating transparency in manufacturing processes by means of appropriate modeling approaches are essential to identify opportunities and threats for investments in digitized value networks.

RP 1 elaborates that current CPPS literature has no common understanding regarding basic CPPS entities and their characteristics, which is required to provide urgently needed CPPS modeling approaches. Therefore, this paper aims to contribute to a common understanding of CPPSs by defining and classifying CPPS entities and illustrating their relations. More precisely, RP 1 applies the iterative development process of Nickerson et al. (2013) to provide (i) a terminology, whereby various terms from literature are considered and processed into definitions for CPPS entities, (ii) a taxonomy, to classify terms within an *is-a-relationship*, and (iii) a reference model, which bases on an *unified modeling language* (UML) class diagram to illustrate abstract relations between CPPS entities (in terms of associations and aggregations). Thereby, the reference model serves as a basis for the provision of more concrete CPPS modeling approaches in future, which are essential for investment risk and return identification in digitized value networks (cf. Figure I.2-1). More precisely, RP 1 addresses objective II.1 from Table I.1-1 by answering the following research questions:

- How can entities in CPPSs be defined?
- How can entities in CPPSs be classified?
- How can relations between entities in CPPSs be illustrated?

Digital transformation in the business sector yields massive increases in demand for cloud computing services as annual cloud market volumes are expected to increase from $246 billion by 2017 to $383 billion by 2020 (Gartner 2017b). Thereby, the highest growth is attributed to *infrastructure-as-a-service* (IaaS) markets due to compute-intensive artificial intelligence, analytics, and IoT (Gartner 2017b). Flexible recourse to external cloud computing services “will enter in all industrial areas” (Bauernhansl 2015, p. 352), since “more and more companies outsource their data and computation tasks to the cloud service provider to greatly reduce the cost" (Cheng and Zhang 2015, p. 2170). Thereby, new IaaS spot markets (such as Amazon EC2 spot instances) with volatile price developments emerge that are typically cheaper than regular IaaS on-demand instances, which base on a fixed price (Kamiński and Szufel 2015). If companies possess temporal flexibility in executing their requests, they can use these spot markets' volatile price development to yield monetary savings.

RP 2 grasps this situation. Elaborating its research gap by analyzing cloud computing literature, RP 2 specializes on variable-time cloud requests on IaaS spot markets considering an exogenously specified deadline. Variable-time cloud requests possess temporal flexibility in execution, though, once started, they must not be interrupted (Vieira et al. 2015). The paper applies discrete-time *real options analysis* (ROA) to evaluate cloud customers' temporal flexibility considering uncertain spot price development and their individual deadlines in job execution. In addition, ROA provides decision support, since, in each discrete time step, the model recommends either to immediately purchase cloud services or to defer the purchase for (at least) one more time increment. Thereby, companies can reduce their costs for external cloud computing services. Following principles of VBM, the value of such temporal flexibility must be considered when companies evaluate and decide on investing in on-premise cloud computing solutions, external cloud computing services, or CPPSs that further enhance temporal flexibility in compute-intensive requests (cf. Figure I.2-1). To sum up, RP 2 addresses objective II.2 from Table I.1-1 and contributes by answering the following research question:

- How can cloud services customers quantify and exploit their short-term demand flexibility's monetary value using ROA, in the light of uncertain price development?

Digitized value networks are composed of several horizontally integrated CPPSs. Thereby, horizontal integration describes "the integration of the various systems used in the different stages of the manufacturing and business planning processes that involve an exchange of materials, energy and information both within a company (for example, logistics, production) and between several different companies in the manufacturing networks" (Liu et al. 2015, p. 111). Due to increasing horizontal integration of CPPSs, digitized value networks are prone to increasing (structural) complexity and interdependencies, which might cause systemic risks. The concept of systemic risks originates from finance and economics literature and describes "how a small shock can wreak havoc in a system" (Scheibe and Blackhurst 2018, p.

44). Systemic risks are integral part of globalization (Goldin and Mariathasan 2014) and can affect many companies within the same industry or even across different industries (Schlegel and Trent 2016). In particular, systemic risks can cause huge supply chain disruptions (Scheibe and Blackhurst 2018), not only due to material dependencies (e.g., due to supplier failure) but also due to information dependencies. For instance, IT-security risks in cloud computing services (Akinrolabu et al. 2018) or CPPS supervisory control (Chhetri et al. 2018) could also trigger huge supply chain disruptions.

RP 3 addresses the increasing need for systemic risk management in digitized value networks. Thereby, the paper elaborates important insights from literature in supply chain risk management, information-based risk management, and DSSs in risk management. These insights are subsequently used to provide a functional design and generic system architecture for risk management support systems designed specifically to manage systemic risks. Thereby, the paper especially emphasizes the importance for such DSSs to gather and share information about and with related supply chain participants and (digital) service providers. However, as there are many unsolved challenges for the further development of such risk management support systems, RP 3 elaborates highly relevant research questions for interdisciplinary researchers and practitioners. In an advanced status of development, such DSSs for systemic risk management could help decision-makers to identify, evaluate, and decide on investments in business relationships, technologies, site selections, and sales markets. Furthermore, decision-makers could continuously evaluate their investment decisions by monitoring their (systemic) risk exposure over time. Therefore, RP 3 contributes to all four process steps of the integrated risk and return management cycle (Figure I.2-1). In accordance with Objective II.3 from Table I.1-1, RP 3 addresses following research question:

- What is an appropriate generic architecture for a DSS that is capable of identifying systemic risks, analyzing those risks, and providing strategic decision support in digitized value networks?

In the following, research papers that contribute to energy flexibility management as subactivities in digitized value networks are embedded in the research context and fundamental research questions are highlighted.

I.2.2 Section III: Decision Support for Risk Management in Energy Flexibility Management

Research Paper 4: *"Providing Utility to Utilities: The Value of Information Systems Enabled Flexibility in Electricity Consumption"*

Research Paper 5*: "Decision Support in Building Automation - A Data-driven Demand Response Approach for Air Conditioning Systems"*

Research Paper 6: *"Demand Side Management: Entscheidungsunterstützungssysteme für die flexible Beschaffung von Energie unter integrierten Chancen- und Risikoaspekten"*

Research Paper 7*: "The Regional and Social Impact of Energy Flexible Factories"*

The transition to renewable energy sources makes energy costs an increasingly important competitive factor for many manufacturing companies (Ecofys 2016; European Commission 2014; Dombrowski and Riechel 2013). Thereby, uncontrollable availability and weak predictability of solar radiation and wind increases electricity price volatility (Wozabal et al. 2016). Conducting DR approaches, companies can exploit their temporal flexibility in externally sourcing electricity to make use of volatile spot market price development and yield monetary savings while contributing to a sustainable energy consumption. Although the modeling of electricity markets is a complex task (Kazempour et al. 2011), evaluating temporal flexibility in electricity consumption considering volatile spot market price development is necessary for companies to evaluate and decide on related investments.

Lowering companies' electricity costs is the overarching objective of RP 4. By analyzing historical spot market price information from the electricity exchange EPEX SPOT, RP 4 illustrates typical intraday patterns in spot market price development. These historical patterns are used to provide a stochastic process for future price predictions, which is the basis for this paper's ROA based on a modification of the binomial tree model of Cox et al. (1979). As purchase of electricity is assumed to be obligatory within a company's temporal flexibility window, the paper models temporal flexibility as an option to defer the purchase (for a certain time). In addition, the DR approach provides decision support, since, in each discrete time step, the model recommends either to immediately purchase electricity or to defer the purchase for (at least) one more time increment. Following principles of VBM, the value of such temporal flexibility must be considered when companies evaluate and decide on investments in energy flexible production technology, battery storages, P2X technology, energy generation, or ICT and DSSs that support energy flexibility management (cf. Figure I.2-1). To sum up, RP 4 addresses objective III.1 from Table I.1-1 and contributes by answering the following research question:

- How can one quantify the monetary value of IS-enabled, short-term flexibility in consumer demand for electricity using ROA?

Buildings are responsible for 21% of the world's total energy consumption and their energy demand is expected to increase by 32% between 2015 and 2040 (U.S. Energy Information Administration 2017). Thereby, electricity demand in the commercial building sector is expected to increase more than 60% between 2015 and 2040 (U.S. Energy Information Administration 2017), whereby *heating, ventilation, and air conditioning systems* (HVAC systems) are among the biggest electricity consumers in the United States (U.S. Energy Information Administration 2018). Therefore, HVAC systems are another promising use case for companies to realize electricity cost savings by exploiting temporal flexibility in the face of volatile spot market price development. However, as HVAC systems can change temperature conditions in buildings only temporarily (due to continuous thermal movement), decision-makers must additionally consider decaying effects of previous HVAC to properly decide on using temporal flexibility.

In this vein, RP 5 addresses the special use case of energy flexible HVAC systems, which the paper refers to as *air conditioning* (a/c) systems. For evaluating temporal flexibility, this paper's DR approach includes short-term prognosis for both spot market price development and a/c electricity demand. While the former bases on typical intraday price patterns that can be observed in historical data, the latter is derived from a regression of historical a/c electricity demand on respective outside temperature development. Applying the regression model, weather forecasts can be used to estimate future a/c electricity demand. As the modeling of both price and demand forecasts increases complexity compared to RP 4, the evaluation of temporal flexibility and the periodical decision support (to either immediately initialize or defer a/c) are both based on a simple minimization of expected total electricity costs. However, even this simplified evaluation of a/c systems' temporal flexibility contributes to existing literature and is useful for decision-makers to evaluate and decide on investments in energy flexible a/c systems or ICT and DSSs that assist respective decision-making (cf. Figure I.2-1). RP 5 addresses objective III.2 from Table I.1-1 and contributes by answering the following research question:

- How can data-driven decision support for load shifting reduce electricity costs in real estate a/c systems?

According to Kagermann (2015), “there will be an unprecedented increase in the complexity of our energy system that we would be unable to manage using today’s methods” (p. 28). Therefore, he suggests the integration of energy technology and ICT (Kagermann 2015). At a company level, ICT enables the establishment of energy efficient (Bunse et al. 2011) and energy flexible manufacturing (Schott et al. 2018). To identify, evaluate, and exploit DR potential with the objective to reduce electricity costs or generate income from selling flexibility on balancing markets, overarching DSSs are required that integrate information from energy markets and energy producing and consuming technologies inside the production environment.

Following this objective, RP 6 derives important functional requirements for DSSs that are supposed to assists decision-makers in companies’ energy flexibility management. Furthermore, the paper presents a generic system architecture for such DSSs that bases on the generic observer/controller architecture of Richter et al. (2006), which serves for the design and analysis of organic computing systems. In this generic system architecture, the integration of market interfaces, energy producers, and energy consumers are described by flows of information that are further processed for optimization. The realization of such DSSs for energy flexibility management would help companies to identify, evaluate, and decide on investments in energy flexible production technology, battery storages, P2X technology, and energy generation. Furthermore, decision-makers could continuously evaluate their investment decisions by monitoring each project’s monetary success. Therefore, RP 6 contributes to all four process steps of the integrated risk and return management cycle (Figure I.2-1). In accordance with objective III.3 from Table I.1-1, RP 6 addresses following research questions:

- What are important functional requirements for a DSS in energy flexibility management that is capable of identifying, evaluating, and exploiting energy flexibility potential?
- What is an appropriate generic system architecture for such a DSS?

Although DR by scheduling manufacturing processes may exhibit large economic potentials for companies, there are further influencing factors that decision-makers must consider when they decide on energy flexibility measures. First, there may be technological restrictions such as limited flexibility in machine control, threats of machinery damages, or downtimes due to maintenance. Second, there may be ecological restrictions such as limit values for emissions or noise. Third, there may be social restrictions such as hour laws, end of shifts, or unreasonable burdens for employees due to energy flexible production. Therefore, a transdisciplinary research approach is required to identify obstacles in energy flexible manufacturing that emerge beyond analysis of economic feasibility. Transdisciplinary research "deals with problem fields in such a way that it can (a) grasp the complexity of problems, (b) take into account the diversity of scientific and life-world perceptions of problems, (c) link abstract and case-specific knowledge, and (d) develop knowledge and practices that promote what is perceived to be the common good" (Pohl and Hadorn 2008, p. 111). A transdisciplinary research approach is in accordance with principles of VBM as it allows decision-makers to take a more holistic view that may influence investment decision-making.

With the objective to utilize companies' energy flexibility and lower their electricity costs, RP 7 presents such a transdisciplinary research approach in which energy flexible factories are viewed in a broader context as important parts of an energy transition to renewable energy sources. Thereby, energy flexibility measures must not only be economically viable but also consider technological, ecological, and social restrictions. Therefore, RP 7 motivates to incorporate scientists and practitioners from industry, politics, administration, NGOs, and citizens to contribute to the design and implementation of energy flexible factories. As this increases the probability of energy flexible factories' general acceptance and conformity with applicable law and regulation, this transdisciplinary research approach is a contribution to investment risk and return identification as illustrated in Figure I.2-1. More precisely, RP 7 addresses objective III.4 from Table I.1-1 by answering the following research question:

- What is an appropriate transdisciplinary approach to utilize (industrial) energy flexibility with respect to technological, ecological and social restrictions?

I.2.3 Section IV: Results and Future Research

After this introduction, which aims at outlining the objectives and the structure of the doctoral thesis as well as at motivating the research context and formulating the research questions, the research papers are presented in Sections II and III. Subsequently, Section IV presents the key findings and highlights areas for future research in the fields of decision support for risk and return management in digitized value networks and energy flexibility management.

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II Decision Support for Risk and Return Management in Digitized Value Networks

Section II deals with investment risk and return management in digitized value networks. As the intensive integration of *cyber-physical production systems* (CPPSs) in digitized value networks yields complex interrelations and interdependencies, companies could benefit from the development of *decision support systems* (DSSs) that assist decision-makers in investment risk and return management following principles of value-based management. However, the realization of such DSSs is a difficult task as these information and communication technologies must be carefully designed and implemented to improve decision-making. *Research papers* (RPs) 1-3 contribute to the development of such DSSs considering specific decision-making situations.

The first research paper (RP 1) *"Organizing Self-Organizing Systems: A Terminology, Taxonomy, and Reference Model for Cyber-Physical Production Systems"* (Section II.1) analyzes digitized value networks on a rather fine-grained level of CPPSs. Thereby, RP 1 enables CPPS modeling approaches in future and contributes to investment risk and return identification, by providing definitions and a classification of CPPS entities and an analysis of their relations.

The second research paper (RP 2) *"Scheduling Flexible Demand in Cloud Computing Spot Markets - A Real Options Approach"* (Section II.2) enables companies to reduce their costs for sourcing of external cloud computing services by providing a real options approach for evaluating and exploiting temporal consumption flexibility. Regarding investment risk and return management, RP 2 contributes to risk and return quantification and control.

The third research paper (RP 3) *"Toward Strategic Decision Support Systems for Systemic Risk Management"* (Section II.3) contributes to systemic risk management by introducing a functional design and generic system architecture for respective DSSs. Furthermore, RP 3 carves out highly relevant research questions for researchers and practitioners. Thereby, this research paper contributes to all four steps of investment risk and return management in an overarching manner.

II.1 Research Paper 1: "Organizing Self-Organizing Systems: A Terminology, Taxonomy, and Reference Model for Cyber-Physical Production Systems"

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Published online in:	Information Systems Frontiers, 1-24. https://link.springer.com/article/10.1007/s10796-019-09952-8

Abstract:

Ongoing digitalization accelerates the transformation and integration of physical production and traditional computing systems into smart objects and their interconnectivity, forming the Internet of Things. In manufacturing, the cross-linking of embedded systems creates adaptive and self-organizing Cyber-Physical Production Systems (CPPSs). Owing to ever-increasing cross-linking, rapid technological advances, and multifunctionality, the complexity and structural opacity of CPPSs are rapidly increasing. The development of urgently needed modeling approaches for managing such complexity and structural opacity, however, is impeded by a lack of common understanding of CPPSs. Therefore, in this paper, we contribute to a common understanding of CPPSs by defining and classifying CPPS entities and illustrating their relations. More precisely, we present a terminology, a taxonomy, and a reference model for CPPS entities, created and evaluated using an iterative development process. Thereby, we lay the foundation for future CPPS modeling approaches that make CPPS complexity and structural opacity more manageable.

II.1.1 Introduction

The tremendous increase of available information that has accompanied the onset of the information age has fundamentally changed our world. With continuing developments in technology, including broadband expansion, improved data processing, and storage performance, the digital revolution has gathered further momentum. One indicator of this development is the ongoing replacement of traditional computing systems with smart objects, which are entering almost all areas of human life. Internet infrastructures are being used to interconnect context-aware physical objects, forming the Internet of Things (IoT) (Kees *et al.* 2015). The potential of the IoT is emphasized by McKinsey, who estimate that the IoT's economic impact will reach nearly $6.7 trillion per year until 2025 (Manyika *et al.* 2013). One use of the IoT is Cyber-Physical Systems (CPSs), which aim to merge physical reality (i.e., the 'real-world') with the information-based digital world (Kagermann *et al.* 2013; Lucke *et al.* 2008; Schuh *et al.* 2014). CPSs consist of several embedded systems (Gräßler *et al.* 2016; Hellinger and Seeger 2011), which integrate software into physical objects and enable intercommunication within the boundaries of systems which are well-defined but which may be geographically distributed. Information exchange is realized through local and global networks, which enhance system functionality and communication range to an unprecedented level (Schuh *et al.* 2014). Beyond the purpose of connection, CPSs are characterized by their interaction with the system's physical environment. Sensors and actors are used to digitally monitor and influence physical processes. The ability of CPSs to perceive and interpret surrounding events enables such systems to interact with human beings and to execute tasks in the physical environment. These capabilities create highly adaptive, cooperative, and self-organizing systems (Hellinger and Seeger 2011; Broy *et al.* 2012; Yoon *et al.* 2012). Such a system can be referred to as self-organizing, "if the system acquires its time, space, and/or functional structure without being influenced by any imposing external element" (Lin *et al.* 2012, p. 92). Hence, "applications of CPS arguably have the potential to dwarf the 20th century IT revolution!" (Lee 2008, p. 363).

The concept of CPS is applied in a multiplicity of disciplines, including automotive systems, avionics, energy distribution, health care, and traffic control (Ahmed *et al.* 2013). In industries, applications of CPSs are frequently researched within what are commonly termed 'Smart Factories'. By managing smart energy concepts, logistics, manufacturing equipment, and products, Smart Factories can improve the efficiency of production processes while minimizing susceptibility to faults (Kagermann *et al.* 2013). A production-oriented application of CPSs within a Smart Factory is called a Cyber-Physical Production System (CPPS). Following Penas *et al.* (2017), we define CPPSs as "systems that synergize conventional production technology and IT, which allow machines and products to communicate with each other in the IoT environment" (p. 55). The main objective of CPPSs is to manage the continuous optimization of (individual or multiple) digitized production processes. Thereby, CPPSs offer the possibility of integrating distributed production processes and various information technology (IT) systems on different levels by performing vertical and horizontal integration (Kagermann *et al.* 2013; Yoon *et al.* 2012). Physically distributed, organizationally integrated production systems can allocate and coordinate customer orders and production resources on a global scale. The dynamic composition of production steps provides increased production flexibility and efficiency, as well as additional sustainable resource and energy management. However, in order to define and delimit a single CPPS, we assume such a system will possess system boundaries (e.g., in terms of specific production steps, geographical locations, or areas of responsibility). Therefore, CPPS entities (i.e., CPPS hardware and software components) are interconnected via a common network infrastructure that reflects these boundaries. The development of CPPSs progressively replaces traditional mass production, and, in turn, intensifies customer-oriented production characterized by small batch sizes, which becomes increasingly economically profitable. However, the management of production systems by cyber-physically integrated, efficient, and flexible CPPSs not only enables cost-saving strategies and new business models. It also creates new challenges which researchers and practitioners must address.

The huge complexity of CPPS presents a major challenge to those involved in its design and implementation (Hellinger and Seeger 2011; Pétrissans *et al.* 2012; Zuehlke 2010). Complexity develops owing to the ever-increasing cross-linking and multifunctionality, which results in structural opacity of integrated embedded systems. Discussing the "Cyber-Physical Design Challenge", National Instruments (2014) confirms this development by stating that "the evolution of a simple design into a complex system is commonplace, but we still struggle to manage complexity while accelerating innovation" (p. 4). Moreover, there is currently no common understanding of CPPSs (Wang *et al.* 2015; Ullrich *et al.* 2016) even though such an understanding is necessary in order to create general models of production, processes, and machines (Hellinger and Seeger 2011) which can efficiently develop CPPSs and overcome their complexity and structural opacity. More precisely, in order to model CPPS, it is essential to define and classify entities (i.e., components) and characteristics (i.e., properties), and to illustrate their interrelations. Modeling approaches require common terminology, especially as CPPSs are an interdisciplinary concept which combines elements of automation, informatics, and (production) engineering (Kagermann *et al.* 2013; Karnouskos and Colombo 2011). Yet, to date, "heterogeneity and isolated [CPPS] solutions prevail" (Hellinger and Seeger 2011, p. 12). The industry experts interviewed in the course of this study confirm that an improved common understanding of CPPS entities, characteristics, and their relations is vital in order to create appropriate modelling approaches that provide guidance for the digital transformation of traditional production environments to CPPSs. As small and medium enterprises are usually more restricted in their budgets, such guidance will help to limit their investments in individual transformation projects. As CPPS characteristics, such as "self-organizing", usually depend on a CPPS's structure, defining and classifying CPPS entities and illustrating their relations is the logical first step. Hence, in this paper, we contribute to a common understanding of CPPS entities and leave further analysis of CPPS characteristics for future research. Moreover, definitions of CPPS entities are necessary for expedient classification. The classification of CPPS entities, on the other hand, is a prerequisite when it comes to illustrating their relations. Therefore, we strive for answering the following research questions:

RQ1: How can entities in Cyber-Physical Production Systems be defined?

RQ2: How can entities in Cyber-Physical Production Systems be classified?

RQ3: How can relations between entities in Cyber-Physical Production Systems be illustrated?

In order to answer these research questions, we define CPPS entities using a common terminology (RQ1), classify these entities using a taxonomy (RQ2), and illustrate their relations using a reference model (RM) (RQ3). In creating and evaluating our terminology, we apply the iterative development process offered by Nickerson *et al.* (2013). We define terminology as "special words or expressions used in relation to a particular subject or activity" (Cambridge Dictionary 2018) (i.e., in our case, used in relation to CPPS entities). A taxonomy is a system which classifies objects in order to help "researchers and practitioners to understand and analyze complex domains" (Nickerson *et al.* 2009, p. 336). We use this scheme to classify CPPSs as it reduces complexity and enables the identification of common capabilities (Bailey 1994). Moreover, a taxonomy provides the basis for examinations of relations between objects (Nickerson *et al.* 2009) that we conduct by developing an RM. Following Frank (1999), we hold that: “A generic reference model represents a class of domains […] and is not restricted to particular instances. Instead it is motivated by the search for general structures that can be applied to numerous instances” (p. 695). Hence, an RM is an “abstract representation of the entities and relationships of a domain which is designed to provide a basis for the development of more concrete models and implementations” (Maldonado *et al.* 2009, p. 562). To implement our RM, we apply a semiformal language known as the Unified Modeling Language (UML). Our terminology, taxonomy, and RM enable an interdisciplinary modeling process which covers different application areas such as engineering and IT; therefore, they contribute to the establishment of a common understanding of CPPSs (Hubka and Eder 2012; Schuette and Rotthowe 1998).

The proposed terminology, taxonomy, and RM (in the following: ‘artifacts’) for CPPS entities (in the following: ‘entities’) build on an extensive literature review, focus group discussions, interviews with experts, and our own critical insights from internal discussions. Researchers and practitioners could apply these concepts in various areas. For example, they might further extend understandings of CPPS by extending our artifacts using characteristics, which will differ depending on a CPPS’s structure. Secondly, as the development of CPPSs “includes issues of communication topology, reference architectures, open architecture and modular service architecture” (Hellinger and Seeger 2011, p. 28), information systems (IS) designers could develop and apply our artifacts when designing CPPS system architectures. In addition, the modeling of CPPS entities is an important step towards modelling subsequent development, engineering, and manufacturing processes (Kagermann *et al.* 2013). In the case of inter-organizational project teams, our artifacts will improve cooperation by facilitating comparability between heterogeneous production and IT environments and cross-company processes. For operational risk management, our taxonomy and RM are important means to identify and analyze risk sources and propagation, e.g., for IT security and IT availability risks. Improved operational risk management can not only reduce the potential for economic damage in the course of high-risk events, but can also support profound economic investment decisions about mitigation measures and prioritization in operational risk control.

Our paper is structured as follows: In Section II.1.2, we present an overview of related work in order to highlight the current research gap. In Section II.1.3, we present our research method and illustrate that evaluation was part of our iterative artifact development. In Section II.1.4, we present our terminology and taxonomy by defining and classifying relevant entities and examining related terms in CPPS literature. In Section II.1.5, we present our RM, which indicates the relations between entities. In Section II.1.6, we demonstrate the usability of our RM by applying it to three fictional and one real-world application scenarios. In Sections II.1.7 and II.1.8, we discuss our results and conclude.

II.1.2 Related Work

In this section, we present related work which provides a foundation for our research. More precisely, we highlight calls within the existing literature for appropriate CPPS modeling approaches, and we illustrate the current lack of consensus regarding CPPS entities and characteristics, the very consensus which would be required to develop new modeling approaches.

Drawing on the expertise of more than 80 contributors, Kagermann *et al.* (2013) explore several challenges to, and recommendations for, the implementation of CPPSs. They emphasize that increasing complexity in CPPSs requires appropriate modeling approaches, the use of which “constitutes an important strategy in the digital world and is of central importance” (p. 42). Gronau *et al.* (2016) use a simulation to determine the optimal level of CPPS autonomy. They stress that common CPPS modeling approaches are necessary to depict a broad variety of different production processes with different production topologies. Monostori *et al.* (2016) state that “modelling the operation and also forecasting the emergent behavior of these systems raises a series of basic and application-oriented research tasks, not to mention the control of any level of these systems” (p. 625). Reviewing the CPS research, which at the time was still in its infancy, Kang *et al.* (2016) examine industrial technology trends and note that the realization of smart manufacturing concepts requires specific modeling approaches.

While existing literature highlights the need for appropriate modelling approaches, it offers no consensus regarding CPPS entities. Chen (2017a) examines the theoretical foundations of CPSs, and describes CPSs as systems of physical and computational entities with communicational, computational, and controlling capabilities. Thereby, the evolution from embedded systems towards advanced CPSs (Gürdür *et al.* 2016) can be viewed as the progressive integration of deeply intertwined physical and computational entities with their surroundings and with production processes (Xu *et al.* 2018). Xu and Duan (2018) stress the need for big data approaches in order to process increasing amounts of data within large CPSs, consisting of sensors, actuators, embedded systems, and humans, to improve efficiency, security, and scalability in industry. Xu *et al.* (2014) note that complex CP(P)Ss integrate "various devices equipped with sensing, identification, processing, communication, and networking capabilities" (p. 2240). Conducting a broad literature review that includes 77 contributions on CPS in different application fields, Chen (2017b) states that "CPS can provide broad controls over complex and large industrial processes through a heterogeneous network architecture of sensors, actuators, and processors" (p. 13). Outlining CPPS research and applications, Wang *et al.* (2015) state that CPPSs integrate an "enormous variety of equipment, ranging from vision systems and sensors to robots and conveyors, including metrology equipment, different controllers, different levels of users, and so forth" (p. 519). Monostori *et al.* (2016) state that "CPPS[s] consist of autonomous and cooperative elements and sub-systems that are connected based on the context within and across all levels of production, from processes through machines up to production and logistics networks" (p. 624). Darwish and Hassanien (2017) categorize entities into human users, user interfaces (GUI, virtual environments), cyber parts (for data storage, monitoring, analysis, modeling, simulation, decision making), network entities (for transferring data input and control actions), and physical parts (physical equipment, actuators, sensors). Kagermann *et al.* (2013) state that CPPSs comprise "smart machines, warehousing systems and production facilities that have been developed digitally and feature end-to-end ICT-based integration, from inbound logistics to production, marketing, outbound logistics and service" (p. 14). According to Imkamp *et al.* (2016), CPPSs integrate the product, the production, and the production system by using multimodal interfaces such as sensor and measurement systems.

As is evident from this brief review of the existing literature, there is, at present, no common understanding of CPPS entities, nor is there a uniform definition of CPPS characteristics. Although the remainder of this paper focusses on entities, we also briefly elaborate on the differing characteristics: Monostori *et al.* (2016) list various CPPS characteristics – including robustness, self organization, safety, remote diagnosis, real-time control, autonomous control, transparency, prediction capabilities, efficiency, and model correctness – along with current challenges in research and development challenges – such as context adaptive systems, cooperative production systems, and human-machine symbiosis. One network of researchers from several universities created a "Concept Map". The project defines CPSs as feedback systems which are: networked and/or distributed with or without wireless sensing and actuation; adaptive and predictive; intelligent; and real-time capable. The authors also note that CPSs may link with economies, environments, and humans (CyberPhysicalSystems 2018). Kagermann *et al.* (2013) describe CPPSs as being “capable of autonomously exchanging information, triggering actions and controlling each other independently” (p. 5). Otto *et al.* (2018) introduce a parameter estimation approach that can be used to develop flexible modular automation software. In particular, they emphasize that CPPSs should be reusable, i.e., they should be able to adapt themselves to various production processes and types of products. Weyrich *et al.* (2017) introduce an evaluative model for CPPS assessment, and identify performance indicators which correspond with CPPS characteristics related to the overall system architecture (modularity, complexity, usability), changing production system (automatic planning, reconfigurability), cyber support (social interaction, support for decisions), and production operations (maintainability, production efficiency, autonomic adaption). Elaborating on the autonomous monitoring and control of CPSs, Zhang *et al.* (2018) propose a smart production logistic system based on a data-driven, analytical model to implement self-organizing configuration mechanisms. Elsewhere, Zhang *et al.* (2017) develop a self-organizing shop floor based on a multi-agent system. To support the design of future systems which account for high levels of uncertainty, Musil *et al.* (2017) elaborate on the realization of self-adaptability, which, in particular, is hampered by the openness, heterogeneity, and large-scale of CPPSs. Overall, there is no consensus about common CPPS entities and characteristics, and the terms described vary significantly in their level of abstraction and context. Hence, appropriate methods must be developed in order to fill this gap.

Although many authors mentioned CPPS entities and characteristics within their research, we were not able to identify any related work concerned with the development of a terminology, a taxonomy, or an RM for CPPS entities. While the “Concept Map” of cyberphysicalsystems (2018) presents CP(P)S characteristics, it falls short of describing and classifying CP(P)S entities and their relations (cyberphysicalsystems 2018). Considering multiple application domains, including smart grids, home networking, and health care, Chen *et al.* (2012) analyze the relations between CP(P)Ss, machine-to-machine communication, wireless sensor networks, and the IoT. The authors build machine-to-machine and communication architectures, which depict only partial aspects of CPPSs and lack a manufacturing context.

Darwish and Hassanien (2017) present an overview of key aspects of CP(P)Ss, and an architecture for CP(P)Ss. However, their approach does not illustrate the interconnections between entities. Based on ten CPS reference architectures, Sánchez *et al.* (2016) propose a CPS-based process control solution for smart manufacturing scenarios. With a focus on – among other things – networks, services, events, and (embedded) devices, the underlying architectures vary significantly in terms of their information content and level of abstraction, and lack both a manufacturing context and a detailed depiction of entities and associated relations. Enabling static and dynamic reconfiguration between CPPS entities, Tomiyama and Moyen (2018) present a design methodology for a resilient CPPS architecture to handle failures in event-driven processes. This architecture lacks a sufficient level of detail concerning entity relations and incorporates only few CPPS entities, i.e., sensors, actors, and controllers. Agostinho *et al.* (2018) develop a CPPS architecture that uses modeling and simulation technologies to integrate data collection and feedback systems into the physical production environment. With a strong focus on sensors and data processing, details on general CPPS entities and their interrelations are missing. Ding *et al.* (2019) propose a framework reference model for CPPS based on digital twin technology. In addition to an input and output layer for product specifications, the framework describes the autonomous behavior of smart parts, shop floor, and manufacturing operations, yet it does not define, or show the interrelations between, entities.

The related works outlined above clearly illustrate that researchers not only use various different terms to describe CPPS entities and characteristics, but that they also employ various levels of abstraction. Most of these terms are neither clearly defined nor classified, nor are the relations between the terms examined. Rather, many authors employ terms describing highly specialized application scenarios, thus focusing on specific aspects and failing to provide a comprehensive overview. This terminological heterogeneity in the literature also indicates a terminological heterogeneity – and, therefore, missing standards – in practice. Overall, heterogeneity impedes the development of urgently needed modeling approaches to managing the complexity and structural opacity of CPPS. This is because the modeling of CPPSs requires a robust foundation of well-defined, classified, and related terms which provide information about the boundaries, abilities, and inner workings of such a system. We address this obstacle by presenting a terminology, a taxonomy, and an RM for entities, enabling the future development of CPPS modeling approaches.

II.1.3 Research Method

The widespread dissemination and use of taxonomies and RMs in IS research emphasizes their potential to contribute to common understandings of specific domains. For example, taxonomies already shed light on evaluation methods for IS artifacts (Prat *et al.* 2015), reputation systems (Hendrikx *et al.* 2015), cloud computing (König und Keller 2014; Sanaei *et al.* 2014), smart things (Püschel *et al.* 2016), big data algorithms (Fahad *et al.* 2014) and projects (Strode 2016), and business-to-thing interaction patterns (Oberländer *et al.* 2017). RMs, on the other hand, have already been used to illustrate relations between domains in cloud services (Martens and Teuteberg 2011), cloud networks (König und Keller 2014), big data analyses (Bornschlegl *et al.* 2016), reputation contexts (Hendrikx *et al.* 2015), agile software development (Gill *et al.* 2018), data management in digital economies (Pentek *et al.* 2017), and critical infrastructures (Bagheri and Ghorbani 2010).

When creating and evaluating our artifacts, we applied the iterative development process formulated by Nickerson *et al.* (2013). Thereby, we conducted several rounds of literature reviews, focus group discussions, expert interviews, and internal discussions. Although it was originally designed for the development of taxonomies, we also used the iterative development process to shape our terminology and RM. The collaborative creation and evaluation of our artifacts was crucial, since the further development of one artifact influenced the other two (and vice versa).

Following Nickerson *et al.* (2013), taxonomy development requires the identification of a meta-characteristic and ending conditions, which remain unchanged throughout the iterative development process (Nickerson *et al.* 2013). The meta-characteristic reflects the domain of interest according to which objects shall be classified. Subjective and objective ending conditions determine when the iterative development process terminates. Each iteration starts with the choice of an appropriate approach, i.e., either the conceptual-to-empirical or the empirical-to-conceptual approach. The conceptual to empirical approach employs researchers' creativity and knowledge of the research field to conceptualize entities and entity dimensions (for classification). Afterward, the research team will examine how (real-life) objects fit with this conceptualization. In contrast, the empirical to conceptual approach requires researchers to study (real-life) objects that are subsequently abstracted and classified in terms of similarities and differences. Nickerson *et al.* (2013) allow the two approaches to be combined within the taxonomy development process. The execution of each approach results in an initial or revised taxonomy for which the predefined ending conditions must be confirmed. The taxonomy development process continues until all subjective and objective ending conditions are met.

In line with our research questions (RQs), we chose CPPS entities as our meta-characteristic for the iterative development process of our taxonomy. As per Nickerson *et al.* (2013), we determined the following objective ending conditions for our taxonomy development: (1) each entity is unique within its dimension, (2) each dimension is unique within the taxonomy, and (3) no new dimensions or entities were added in the last iteration. We also determined the following subjective ending conditions: Our terminology, taxonomy, and RM must be concise (i.e., limited number of terms, classifications, and relations, for reasons of comprehensibility and simplicity), robust (i.e., enough terms, classifications, and relations to model different kinds of CPPSs), comprehensive (i.e., complete, in that it must include all relevant terms, classifications, and relations), extendible (i.e., placing no restrictions on future extensions of our artifacts), and explanatory (i.e., allowing for a suitable instantiation of real-world examples with our taxonomy and RM) (Nickerson *et al.* 2013). We followed Nickerson *et al.* (2013) and chose to combine the conceptual-to-empirical and empirical-to-conceptual approach (depending on our development iteration, cf. below). For the identification of entities, we applied an information-driven perspective and required entities to be either information receivers or transmitters (or both). This is reasonable because information is the key element of CPPSs, and is responsible for relations between entities within the proposed RM. In total, we conducted four iterations to develop our three artifacts (Figure II.1-1).

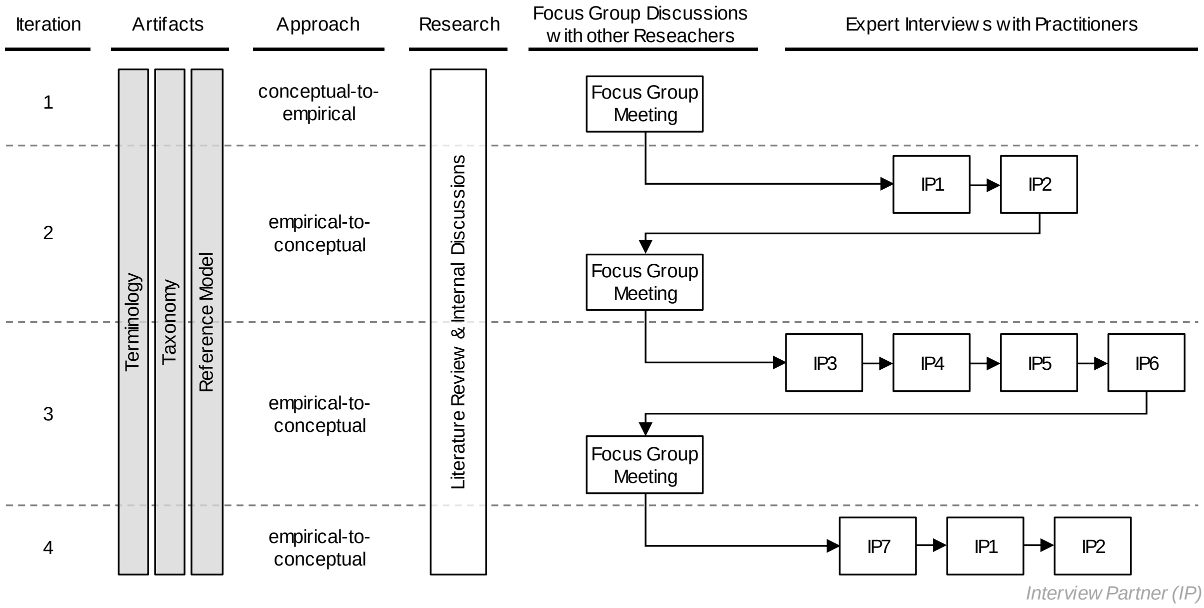

Figure II.1-1: Iterative development process for our terminology, taxonomy, and reference model

As CPPSs are an emerging and interdisciplinary field of research and practice, it is important to develop and evaluate our artifacts with both researchers and practitioners. Therefore, we alternated our literature reviews and internal discussions with focus group discussions involving other researchers, and semi-structured interviews with industry experts. A focus group discussion is a flexible and effective methodology for collecting feedback on artifact improvement and demonstrating the artifact's utility (Tremblay *et al.* 2010). This method allows participants to alternately critique and build on the statements of others in an open discussion (Krueger and Casey 2014). It is suitable for evaluations involving researchers, who will be accustomed to receiving reviews of research artifacts from different perspectives based on a wide range of expertise. An expert interview is a suitable method for collecting first-hand information from potential applicants, i.e., "insights into or understanding of opinions, attitudes, experiences, processes, behaviors, or predictions" (Rowley 2012, p. 261). For our discussions with practitioners, we chose expert interviews as we were particularly interested in the expert's personal experiences. For both methods, we developed semi-structured questions about the predefined subjective ending conditions. Yet, despite our use of predefined questions, we attempted to avoid limiting the experts' feedback on any specific area.

Our chosen focus group of researchers consisted of one distinguished and two associate professors and six research assistants, all drawn from two different universities (excluding the authors). All participants are involved in IS research with a professional focus on digitalized value networks, IoT, business process management, and IT strategy. We ensured that the industry experts we selected for interview (Table II.1-1) met the following criteria: Their sector of industry represents at least one of the three CPPS domains of automation, informatics, and (production) engineering; their company is familiar with the topic of (controlled) self-organizing and distributed systems, and the resulting challenges; they work in a strategic position which enables them to provide an extensive overview of their company's activities and objectives; they have experience with the digitalization of processes in an interdisciplinary environment, and multiple points of contact with other CPPS relevant domains. The focus group discussions were standardized to last 1.5 hours, while each of the expert interviews lasted between one and two hours. Except for the first focus group, we used these discussions with other researchers to discuss the feedback from previous industry expert interviews before we adjusted our artifacts.

In the following, we provide some brief information on our four artifact development iterations. For detailed feedback from industry experts and focus group members, please refer to Appendix A Table II.1-2.

IP	Role of the Interviewee	Industry	CPPS Know-how	Employees (2016)	Revenue (2016)
IP1	Head of IT Project Planning	Robotics	Digital transformation of production processes	> 12,300	EUR 2.9 bn.
IP2	Principal IT Architect	Technology	Hardware, software, and services for CPPSs	> 150,000	EUR 40.0 bn.
IP3	Head of Supply Chain Management & Product Data Management	Fixing Technology	Digital transformation of logistics and production processes	> 25,000	EUR 4.0 bn.
IP4	IT Enterprise Architect	Automotive	Digital transformation of production processes	> 124,000	EUR 94.2 bn.
IP5	Managing Consultant (inter-divisional strategic planning)	IT Service Provider	IT transformation in interdisciplinary industry projects	> 400	EUR 0.1 bn.
IP6	Managing Consultant (IT Architect)				
IP7	Head of Digital Transformation	Automotive	Digital transformation of production processes	> 1,000	EUR 0.1 bn.

Table II.1-1: Details on interviewed experts

As real-world examples of CPPSs are still scarce, we decided to begin the first iteration of our development process by applying the conceptual-to-empirical approach. In the course of our comprehensive literature review, we examined research papers, studies, research projects, and model factories. Based on this examination, we began to conceptualize entities and entity dimensions in a first draft of our artifacts, which captured the first distinct features of CPPSs and served as a basis for the following iterations. Within our first focus group meeting, we discussed our findings.

In order to revise our initial drafts, we conducted a second iteration following the empirical-to-conceptual approach. In accordance with von Briel and Schneider (2012), Gregor (2006), and Williams et al. (2008), we clustered real-life objects to our taxonomy's entities and entity dimensions in order to enhance its structure. With little information about existing (real-world) applications of CPPSs, we had to supplement our literature findings and initial focus group discussion by gaining in-depth knowledge about organizations dealing with CPPS topics. Therefore, we conducted two (separate) interviews with industry experts, followed by another focus group meeting. In addition to validating our artifact drafts, these two experts shared initial practical insights into possible future CPPS applications within their company. Together with the two industry experts and focus group members, we then refined our taxonomy and RM by mapping possible future CPPS applications to entities and dimensions and discussing their relations.

As the revised artifacts did not meet all of the objective and subjective ending conditions, we repeated the empirical-to-conceptual approach in a third iteration. In the second iteration, we had adjusted our artifacts in response to a further literature review, four expert interviews, and a final focus group meeting. Afterwards, as the third objective ending condition (i.e., no new dimensions or entities were added in the last iteration) and the subjective ending conditions were not met, we conducted a fourth iteration, once more applying the empirical-to-conceptual approach. Again, we adjusted our artifacts in response to a literature review and three expert interviews. Two of these three expert interviews were conducted with the interview partners we had previously questioned in the second iteration. As our artifacts had developed since our last interview, we were able to discuss some new insights with both experts and close this feedback loop. With only minor changes, we agreed with these two interview partners that we had met all subjective and objective ending conditions. Accordingly, we refrained from conducting another iteration and completed the development process of our artifacts.

II.1.4 Development of Terminology and Taxonomy

II.1.4.1 Basic Structure of CPPS

In order to define and classify CPPS entities, we apply a framework that provides guidance and structure to the following sections. We categorize entities in five basic entity dimensions (Figure II.1-2) which we formed during our iterative artifact development process. Thereby, we define an entity dimension as a generic category that contains one or several entities. Following Zamfirescu *et al.* (2014), we distinguish dimensions for *human*, *cyber*, and *physical* entities. To account for interactions between these dimensions, additional dimensions are required. Hence, we identify the two interconnecting dimensions of *Human-System Interface* and *Bridging Component*.

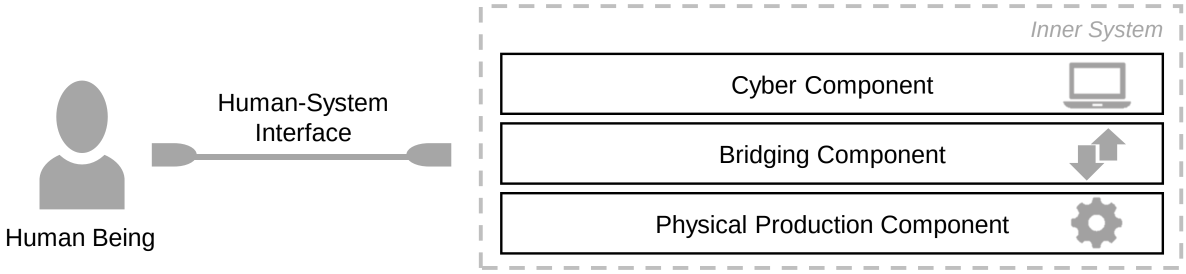

Figure II.1-2: Dimensions of CPPS entities

A CPPS is typically involved in complex multi-level manufacturing processes. All tangible assets that directly contribute to the value-adding process are included in the dimension *Physical Production Component* (Hellinger and Seeger 2011; Kagermann *et al.* 2013; Broy *et al.* 2012). Thereby, Physical Production Components are increasingly supported by IS. The corresponding entities fall under the dimension *Cyber Component* (Hellinger and Seeger 2011; Kagermann *et al.* 2013; Broy *et al.* 2012). Whereas Physical Production Components rely on measures such as mass and energy, Cyber Components are driven by electronic signals. To close this semantic gap, the establishment of an intermediate dimension is required. Following Hao and Xie (2009), we introduce the dimension *Bridging Component*. Entities in this dimension translate signals between Physical Production and Cyber Components to account for mutual interference. We refer to the resulting structure of Physical Production, Cyber, and Bridging Components as the *inner system* of CPPSs. The inner system enables autonomous manufacturing processes to function as an enclosed system. We do not consider the inner system as a separate dimension; however, the term benefits subsequent explanations. Although the vision of CPPSs is to create self-organizing systems, the human being remains central (Zuehlke 2010). An individual may have multiple interactions with the inner system. The importance of this relation is frequently stressed in the literature. However, different approaches vary on whether human being should be included as an integral part of CPPSs or regarded as a separate element (Haque *et al.* 2014). For our proposed artifacts, we follow Zamfirescu *et al.* (2014) and consider the human being as a collaborative and intrinsic element of CPPSs, i.e., we explicitly model the dimension of *Human Being*. As digitalization makes manufacturing increasingly complex and opaque, interfaces are necessary to support the human interaction with the inner system (Hubka and Eder 2012). In particular, there is a need for the monitoring of system properties and states, and the translation and forwarding of human commands to the inner system. The corresponding entities are summarized under the dimension *Human-System Interface* (Kagermann *et al.* 2013).

II.1.4.2 Terminology and Taxonomy for CPPS Entities

As a result of our iterative development process, we structure our taxonomy into two different lanes of granularity, i.e., levels of abstraction (Figure II.1-3). The first lane includes the above-mentioned entity dimensions. The second lane presents highly relevant entities for each dimension. Entities in different lanes are connected within an “is-a relationship”, moving from specific to general terms, e.g., “a Product Component is a Physical Production Component which is a CPPS Entity”. During our iterative development process, we chose to forgo the structuring of entities beyond this level of abstraction in order to guarantee that our output was clear and comprehensive. In accordance with Nickerson *et al.* (2013), we ensure our results are comprehensive by including all entities of interest, i.e., we include all objects that have an immediate influence on the structure and functionality of CPPSs.

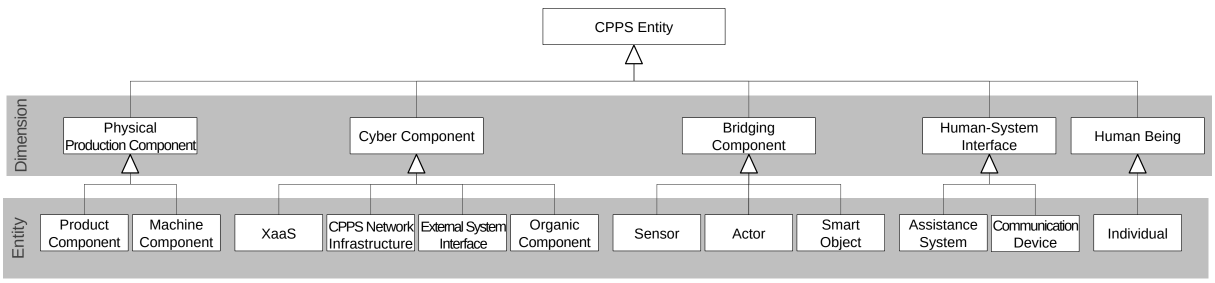

Figure II.1-3: Taxonomy of CPPS entities

In the following, we define the terms used to refer to entities and entity dimensions (RQ1), and classify entities within dimensions (RQ2). Thereby, we establish the means to illustrate relations between entities (RQ3), which are the subject of our RM in Section II.1.5.

II.1.4.2.1. Physical Production Component

We use “Physical Production Component” as an umbrella term for all tangible production assets that actively or passively participate in the production process in order to add value. In CPPS literature, other terms used in place of “Physical Production Component” are “real world” (Bocciarelli *et al.* 2017), “physical world” (Imkamp *et al.* 2016), “physical layer” (Zhu *et al.* 2011), “physical component” (Thiede *et al.* 2016), “physical stack” (Sadeghi *et al.* 2015), “physical object” (Shafiq *et al.* 2015), “physical technology” (Horvath and Gerritsen 2012), and “physical part” (Darwish and Hassanien 2017).

At the entity layer of our taxonomy, we define a *Machine Component* as “a piece of equipment with several moving parts that uses power to do a particular type of work” (Cambridge Dictionary 2018). In CPPS literature, terms used in place of “Machine Component” are “machine” (Sadeghi *et al.* 2015), “machinery” (Thiede *et al.* 2016), and “physical equipment” (Darwish and Hassanien 2017). The term “Machine Component” is used to refer to production machines (e.g., machines to transform or assemble raw material and (semi-)finished products), auxiliary machines (e.g., logistic systems to transport raw material and (semi-) finished products), cross-sectional technologies (e.g., air-conditioning and compressed air systems), and storage systems (Shafiq *et al.* 2015). In CPPS literature, further, more specific terms (used to refer to production and auxiliary machines, in particular) are “robotic machinery” (cyberphysicalsystems 2018), “robotics” (Ma *et al.* 2017), “conveyors” (Wang *et al.* 2015), “transportation means” (Gronau and Theuer 2016), “machine tool”, and “automated guided vehicles” (Darwish and Hassanien 2017).

Secondly, we define a *Product Component* as a key subject of industrial value creation, which comprises raw materials and (semi-)finished products. Raw materials are the unprocessed substances which form an integral part of every tangible asset. Semi-finished products are partially-processed raw materials which have not yet been assembled to form a finished product. Similar terms used in place of *Product Component* are “product” (Imkamp *et al.* 2016) and “manufactured product” (Gaham *et al.* 2015).

II.1.4.2.2. Cyber Component

We define “Cyber Component” as an umbrella term referring to all hardware and software (IS) components which serve the purpose of collecting, storing, analyzing, processing, or securing data within a CPPS. These IS components contribute to communication, computation, and control, forming the “three Cs” of CPSs (National Instruments 2014), and enable major CPPS characteristics such as adaptiveness, self-organization, and context-awareness. In CPPS literature, “Cyber Components” are also referred to as “cyber world” (Imkamp *et al.* 2016), “cyber stack” (Sadeghi *et al.* 2015), “cyber part” (Darwish and Hassanien 2017), “cyber layer”, “cyber technology” (Horvath and Gerritsen 2012) and “system layer” (Zhang *et al.* 2017).

Today, small and medium enterprises primarily use local in-house IS (Holtewert *et al.* 2013). Compared with external services, in-house IS offers the advantages of independence from external providers, full control over sensitive data, and a high degree of specialization. At the entity layer of our taxonomy, we therefore initially intended to define a *Local IS Component* for local hardware and software, such as local data storage, simple processing capabilities, and basic operating software for production machines. During our artifact development process, however, we concluded that a Local IS Component would not deliver any new insights, since most of the entities related to the dimensions of the inner system and Human-System Interface inherently include local hardware and software. Hence, we regard Local IS Components as a prerequisite for the digital transformation to CPPSs and, in this case, abstain from explicit modeling.

We define an *Organic Component* as a software system that makes a CPPS “aware of its own capabilities” and adaptive “to changes in the environmental conditions, in particular with respect to human needs” (Tomforde *et al.* 2011, p.326). The respective CPPS characteristic is also referred to as “controlled self-organization” (Schmeck *et al.* 2010). CPPSs that integrate Organic Components are goal-orientated, agile, and act both autonomously and together with humans (Strohmaier and Rollett 2005). Organic Components include diagnosis and machine learning algorithms (Niggemann and Lohweg 2015) which enable CPPSs to independently adapt to changes in the production environment. We derived the term for this entity from the IS research field of organic computing, which involves “the technical usage of principles observed in natural systems” (Müller-Schloer 2004, p. 3). An Organic Component can apply concepts such as the generic observer-controller architecture as proposed by Branke *et al.* (2006), in which case, it consists of an “observer” that frequently monitors a “system under observation and control” (i.e., in our case, production processes), and a “controller” that frequently optimizes and executes interventions (in production processes), in order to achieve (human) system objectives (Branke *et al.* 2006). CPPSs that involve Organic Components are also referred to as "biological manufacturing systems" (Monostori *et al.* 2016). In the CPPS literature, other terms used to refer to Organic Component are "intelligent computation system" (Sadeghi *et al.* 2015), "intelligent control component" (Zhu *et al.* 2011), "intelligent data processing" (Chen *et al.* 2012), "computing unit" (Wang *et al.* 2008), and "virtual component" (Thiede *et al.* 2016).

To reduce idle and operating costs for IT infrastructure, software development costs and license fees, and to guarantee flexible and unlimited use of hardware and software components, enterprises can source IT services externally. We introduce *XaaS* ("everything as a service") as another entity, which is a "term for the extensive variety of services and applications emerging for users to access on demand over the Internet" (Paasivaara *et al.* 2014, p. 16). It comprises SaaS (software as a service), PaaS (platform as a service), and IaaS (infrastructure as a service), and is "a core component of cloud computing" (Castro-Leon and Harmo 2016, p. 29) that "will enter in all industrial areas" (Bauernhansel 2015, p. 352). Real-time processing of information with cloud computing enables the development of smart factories (Bauernhansel 2015) as cloud computing is capable of providing "on-demand computing services with high reliability, scalability, and availability in a distributed environment" (Xu 2012, p. 75). To increase data security and mitigate privacy issues, organizations may also deploy XaaS as private clouds for exclusive use of servers that "may be owned, managed, and operated by the organization, a third party, or some combination of them, and may exist on or off premises" (Mell and Grance 2011, p. 3). In CPPS literature, other terms for XaaS are "cloud services" (Wang *et al.* 2015) and "Anything as a Service" (Kuehnle 2014).

We define the *CPPS Network Infrastructure* as the entirety of hardware and software components that enables object-to-object interactions within the inner system of a CPPS. This explicitly excludes interactions between human beings and the inner system, which are covered by the dimension "Human-System Interface". We make this distinction to emphasize the key roles of human users, both as part of CPPSs and in exchanging information with the inner system. According to Chen *et al.* (2012), the idea of networking objects involves two basic principles: Firstly, that interconnected objects have more value than stand-alone objects; Secondly, that, as the number of interconnected objects increases, the system's ability for self-organization and intelligent behavior also increases. In contrast to all other entities, we require that the CPPS Network Infrastructure is unique, i.e., exactly one instance of this Cyber

Component exists within every CPPS. This requirement is necessary to limit a CPPS's system boundaries. Such boundaries define which components belong to a single CPPS, and therefore create a framework for designing and modeling CPPSs. Each CPPS Network Infrastructure includes either one central network node or several distributed network nodes, and all peer-to-peer connections (e.g., machine-machine links) that do not necessarily have to be connected with each other. Moreover, due to the fact that CPPSs may span multiple production sites and/or organizations, the CPPS Network Infrastructure can connect geographically distributed entities. If entities are geographically close to one another, they can use encrypted communication via local area wired or wireless networks and wireless sensor networks (Sveda 2014). Otherwise, the CPPS Network Infrastructure must use the internet and/or peer-to-peer network communication, both of which are able to share huge amounts of information among locally distributed systems (Hawa *et al.* 2017). Therefore, the CPPS Network Infrastructure comprises physical cables, wireless communication, bluetooth (Darwish and Hassanien 2017), network adapters (Wang *et al.* 2008), network routers (Zhu *et al.* 2011) and their firmware, and network protocols (Vogel-Heuser *et al.* 2014). In CPPS literature, other terms used to refer to CPPS Network Infrastructure are "CPPS network" (Vogel-Heuser *et al.* 2014), "network" (Darwish and Hassanien 2017), "networking" (Sadeghi *et al.* 2015), "network unit" (Wang *et al.* 2008), "network layer" (Zhu *et al.* 2011), and "CPS network infrastructure" (Yang *et al.* 2017).

A special characteristic of CPPSs is their ability to connect with multiple other external systems beyond their system boundaries, such as other CPPSs and Enterprise Resource Planning (ERP). We define an *External System Interface* as an entity that enables intersystem communication by coordinating and controlling information flows using the Ethernet and IP networks (Schlechtendahl *et al.* 2015). In "systems of systems", CPPSs can globally link within constantly changing system boundaries (Barot *et al.* 2013; Broy *et al.* 2012). Thereby, large-scale systems with increasing functionalities (and complexities) are created and additional external services are made available by integrating next generation internet (Chen *et al.* 2012; Ahmed *et al.* 2013). In CPPS literature, other terms for External System Interface are "gateway" (Schlechtendahl *et al.* 2015), "cross-layer infrastructure" (Foehr *et al.* 2017), and "connection to other systems" (Monostori 2014).

It is important to notice that digital communication through the CPPS Network Infrastructure and, in particular, External System Interfaces requires strategies for CPPS protection. This is because security and privacy issues are major IoT (and therefore CPPS) challenges that may negatively influence the adoption and diffusion of such technologies (Whitmore *et al.* 2015; Sedeghi *et al.* 2015; Ma *et al.* 2017). Examples of existing approaches to CPPS protection include “access control, patching, firewalls, and encryption” (Ullrich *et al.* 2016, p. 1) for Cyber Components and “layered and moving-target defenses” (Ullrich *et al.* 2016, p. 4) for Physical Production Components. Despite its importance, we regard CPPS protection to be part of Local IS (e.g., user authentication systems for applications, or intrusion detection systems as part of a firmware for programmable logic controllers) and, therefore, do not explicitly mention respective entities within the proposed terminology, taxonomy, or RM.

II.1.4.2.3. Bridging Component

Following Hao and Xie 2009, we introduce “Bridging Component” as an umbrella term for entities that “interact with hardware and software components and fill the semantic gap between hardware and software components by propagating events across the hardware/software semantic boundary” (p. 233). By relaying information between Physical Production and Cyber Components, Bridging Components enable bidirectional interaction through digitized events. On the one hand, they identify, locate, and measure Physical Production Components in order to bind these entities and the corresponding information to their virtual representation. On the other hand, they translate control signals into physical actions (Akanmu *et al.* 2012). In CPPS literature, other terms used to refer to Bridging Component are “bridge component” (Hao and Xie 2009), “intermediate component” (Yao *et al.* 2017), “enabler” (Thiede *et al.* 2016), “synergic technology” (Horvath and Gerritsen 2012), and “sensor and actuator networks” (Kuehnle 2014).

We define a *Sensor* as an entity that observes system states and changes in the physical environment, and transforms the gathered information (using microprocessors that are integrated in transducers) into electronic signals for further data processing (Akyildiz and Kasimoglu 2004; Kagermann *et al.* 2013; Berger *et al.* 2016). Hence, Sensors are the CPPS’s “organs of perception”. Sensors can observe one or multiple measurands, such as temperature, humidity, gravity, magnetic fields, motion, or light, and “will take a key role in [future] manufacturing” (Berger *et al.* 2016, p. 638). In CPPS literature, other terms for Sensor are “sensing technology” (Zhang *et al.* 2017), “measurement technology” (Imkamp *et al.* 2016), “metrology equipment” (Wang et al. 2015), and “measurement systems” (Meisen *et al.* 2016).

We define an *Actor* as an entity that translates electronic signals into interventions within the physical production environment. More precisely, an energy-adjusting element within each Actor physically converts received electronic signals from the cyber world which are then performed as specific mechanical movements. According to Nof (2009), Actors can be differentiated according to the seven main types of mechanical movements induced: spring, valve, electricity, magnetism, hydraulics, pneumatics, and thermal energy. Their working method determines whether Actors work either in isolation on single-actor tasks or together on multi-actor tasks (Akyildiz and Kasimoglu 2004). In the CPPS literature, other terms for Actors are “actuators” (Zhu *et al.* 2011) and “actor technology” (Strang and Anderl 2014).

Another entity within the dimension “Bridging Component” is the *Smart Object (SO)*. An SO is a physical component that integrates an IS. However, the literature provides various definitions of SO capabilities (López *et al.* 2011; Vasseur and Dunkels 2010). For our purposes, we follow Fortino *et al.* (2014) who define an SO as an “autonomous, cyber-physical object augmented with sensing/actuating, processing, storing, and networking capabilities” (p. 86). Yet, we extend this definition and require an SO to possess at least one Organic Component and one Physical Production Component. The SO can integrate Sensors and Actors using its Physical Production Component and networking capabilities through a connection of the Physical Production Components to the CPPS Network Infrastructure. The SO can also access data storage and processing capabilities using Local IS or XaaS (usually cloud solutions in smart factories). With the use of physical or digital tags, such as RFID-tags, bar codes, or the assignment of an IP-address, for the identification of, and communication between, objects, a digital representation of the SO’s Physical Production Components is created (López *et al.* 2011; Fescioglu-Unver *et al.* 2015). In CPPS literature, other terms used to refer to SOs are “smart physical objects” (Cena *et al.* 2019), “smart machines” (Kagermann *et al.* 2013), “intelligent machine” (Shafiq *et al.* 2015), and “software enhanced machinery” (Almada-Lobo 2016) which integrates Organic and Mechanical Components. From a product perspective, the terms “intelligent product” (Vogel-Heuser *et al.* 2014), “smart product” (Almada-Lobo 2016), and “smart material” (Kumar and Kumar 2013) refer to the integration of Organic and Product Components.

II.1.4.2.4. Human-System Interface

We use “Human-System Interface” as an umbrella term for entities which enable (authorized) human beings to interact with the CPPS’s inner system. Such interaction comprises “novel forms of collaborative factory work" and the application of "smart assistance systems with multimodal, user-friendly user interfaces" (Kagermann *et al.* 2013, p.23). In CPPS literature, similar terms for Human-System Interface include "human machine interface" (Monostori *et al.* 2016), "user interface" (Darwish and Hassanien 2017), and "presentation layer" (Kassner and Mitschnag 2015).

The ongoing integration of IS in CPPSs increases the complexity of systems. This sets implicit limits on technological progress, as the complexity of a system should not exceed its users' understanding (Kagermann *et al.* 2013). Hence, we define an *Assistance System (AS)* as an entity that enables the reduction of complexity within human-system interaction (cognitive AS) and relieves individuals from physically demanding tasks (physical AS) (APPsist 2018; Kagermann *et al.* 2013; Prem *et al.* 2014). Thereby, "collaboration with intelligent agents, robotics and use of augmented reality systems can assist staff to find greater meaning in their work roles" (Bednar and Welch 2019, p. 14). A cognitive AS is software that supports information and knowledge management (APPsist 2018; Jasperneite and Niggemann 2012). On the one hand, a cognitive AS collects, documents, and processes information for the human user. Such information can then be analyzed and presented in an accessible manner. On the other hand, a cognitive AS allows the user to control the operation of single machines or entire production systems. Cognitive ASs may also enable users to reduce machine setup and commissioning times via the use of plug & play (or plug & produce) approaches. Further, Cognitive ASs may collect data on plant behavior for predictive maintenance, and identify anomalies (e.g., wastage) and the causes of faults. If Cognitive ASs integrate Organic Components, they may even be able to observe and analyze CPPS information, and recommend appropriate control actions in real-time under consideration of constraints set by humans. In contrast to Cognitive ASs, Physical ASs are hardware and software that support human beings by taking on monotonous and/or physically demanding work. For example, service robots may be put to work in assembly and transportation. The fusion of man and machine, via the use of 'exoskeletons', is not only possible but already taking place in some industries (e.g., for installing car seats in automotive industries). In CPPS literature, other terms for AS are "human assistance" (Wang *et al.* 2015) and (for cognitive AS) "decision support system" (Gaham *et al.* 2015).

We define a *Communication Device* as hardware that translates either human input information into electronic signals for the CPPS's inner system and ASs, or system output information vice versa. Human input information may be provided by, among other things, the user's touch, gesture, or voice, while system output information may be provided by, for example, visualization, acoustics, or motion. Examples of this entity are touch-screens, keyboards, buttons, and levers for input information, and computer screens, head-mounted displays, speakers, and signal lights for output information. In CPPS literature, other terms for Communication Device are "communication tool" (Kassner and Mitschnag 2015) and "user device" (Kuehnle 2013)

II.1.4.2.5. Human Being

Human beings, who we consider to be an integral part of CPPSs, observe and control the production's operating systems in order to guarantee congruency between human objectives and constraints. At this point, we have introduced multiple entities that are essential to the technical operation of a CPPS. Focusing on the role of human users, there are three main scenarios in which interaction between humans and the inner system occur: automation, hybrid, and specialization scenarios (Dworschak and Zaiser 2014; Zamfirescu *et al.* 2014). In an automation scenario, most tasks involved in observation and control are performed by Organic Components, which act in a self-organizing manner. Human beings are guided by the system to perform executive operating activities. Conversely, in the specialization scenario, human beings use CPPSs merely as tools which provide support in the decision-making process and improve the efficiency of production processes. The hybrid scenario combines these two scenarios. In this case, tasks involving observation and control are performed by both the inner system and human beings, working together in a cooperative fashion. The choice of interaction scenario will depend on business objectives, branch of industry, technological progress and feasibility, costs, and (social) ethics.

We refer to entities in the dimension "Human Being" as *Individuals*. By clustering actions performed by Individuals, different user roles can be identified, for example, business, operation, engineering, maintenance, and training (Karnouskos *et al.* 2012).

II.1.5 Development of Reference Model

Our RM can be applied to various types of CPPSs as it provides an abstract scheme for relations between classified entities. To illustrate these relations, we use suitable notation elements of the Unified Modeling Language (UML). In addition to its use in structuring code, the UML is appropriate for modeling systems in a non-technical manner. We apply a UML class diagram, which is the "most important structural model and indeed the central model of the UML" (Kiewkanya and Muenchaisri 2011, p. 84). Following the notation of UML class diagrams, all entities are illustrated using classes. A class is a container for a number of objects that share specific characteristics, semantics, and behavior (OMG 2011). Relations between classes (and therefore objects) are plotted by associations, which indicate possibilities for information exchange, and aggregations, which indicate possibilities for entity integration. An aggregation is a "whole-part" relation where a "whole" is composed of multiple "parts". Thereby, a part can exist without the whole. For the proposed RM, we include neither characteristics and methods (i.e., activities) of the classes nor navigations and cardinalities of the class relations, as the RM should be as general as possible (Frank 1999). Our proposed RM for CPPS entities is illustrated in Figure II.1-4.

ASs and Communication Devices enable human interaction with the inner (production) system by executing observation and control tasks (Zamfirescu *et al.* 2014). Individuals can perform three types of interaction: human-machine, human-computer (APPsist 2018), and human-human (Dumas *et al.* 2005). Human-machine interaction describes an Individual who is interacting with a Machine Component (e.g., a production machine or a band conveyor) using one or several Communication Devices (e.g., an on/off switch or a rotary control) which are part of this Machine Component (not necessarily in a spatial context). Human-computer interaction describes an Individual who is interacting with an AS (e.g., cognitive assistance software in a central control panel or a SmartPad) using one or several Communication Devices (e.g., a touch screen, a keyboard, or a monitor) that are part of this AS. In addition, our RM must consider human-human interaction, i.e., collective work involving two or more individuals which "is characterized by its fluidity and complex weaving of organizational, social, political, cultural, and emotional aspects" (Dumas *et al.* 2005, p. 38). An AS could also be part of a Machine Component (e.g., cognitive assistance software in a local control panel, as part of a production machine). Not every CPPS must possess ASs. However, in an automation scenario (cf. Section II.1.4.2.5), they become more important as the inner system can only be controlled via predefined interfaces (Mikusz 2014). Within the proposed RM, such an interface would be the connection of ASs with the unique CPPS Network Infrastructure. The CPPS Network Infrastructure can also connect Machine and Product Components, i.e., entities of the dimension of Physical Production Components. This connection is necessary to allow for remote control (e.g., a central control panel that interacts with a machine's local operating software), remote information access (e.g., a central control panel that accesses a machine's local data storage), and machine-machine communication (e.g., for mutual exchange of information, and collective behavior). Machine and Product Components integrate Actors and Sensors, and we assume that a Machine Component will include at least one Actor; otherwise, the Machine Component would not be able to participate in the value creation process of the smart factory. Actors and Sensors do not have to be accessed by a Machine or Product Component's local operating software. It is also conceivable that they could be accessed directly via other entities (e.g., a central control panel) using the CPPS Network Infrastructure; therefore, the RM must possess additional associations between the Actor/Sensor and the CPPS Network Infrastructure Component. In addition, the CPPS Network Infrastructure can connect with XaaS (e.g., for central data storage or to perform complex computation tasks) and External System Interfaces (e.g., for inter-CPPS communication or to connect with an ERP system), and can therefore incorporate these entities within CPPS boundaries. Organic Components (e.g., software enabling the controlled self-organization of production processes) may be part of ASs, XaaS (e.g., a manufacturing execution system that works on cloud infrastructure), and Physical Production Components (e.g., smart band conveyors, which transport material depending on production machine utilization, or smart, semi-finished products, each of which possesses a virtual twin in a multi-agent system for single-item planning and local production optimization). Because we want to emphasize the central importance of SOs within CPPSs, we integrated a corresponding entity within the proposed RM, although an explicit representation would not have been necessary (instead we could have drawn an aggregation between Organic Components and Machine and Product Components).

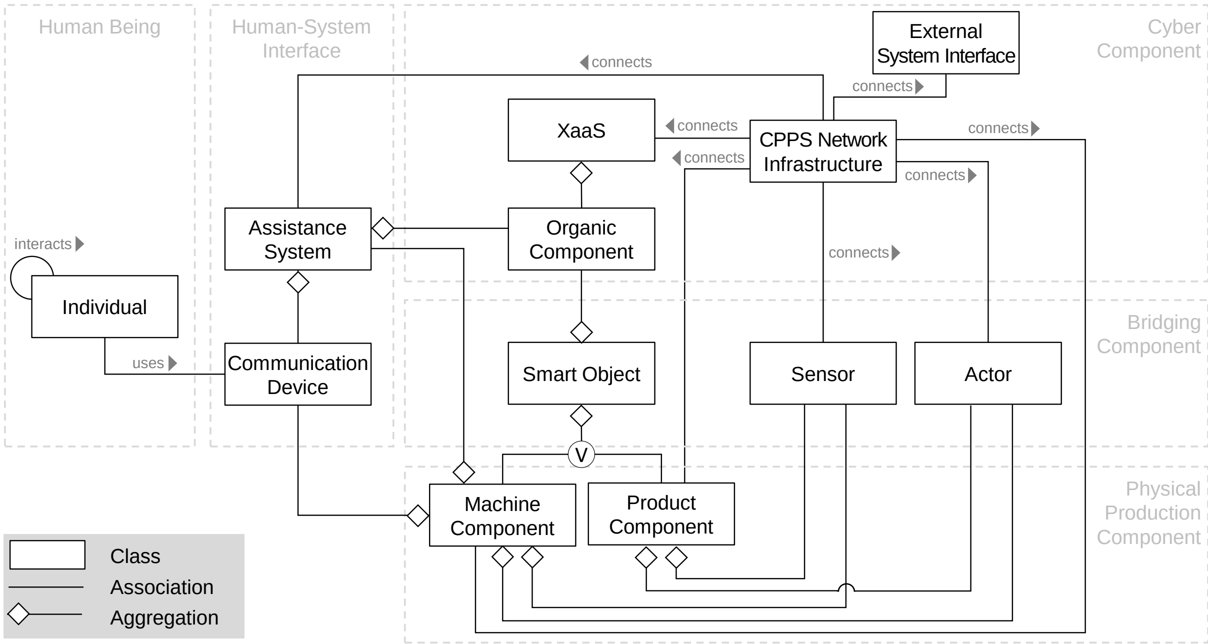

Figure II.1-4: Reference model for CPPSs

II.1.6 Application of the Reference Model

In the following, we demonstrate our RM's efficacy and general applicability. To do so, we present three fictional application scenarios involving CPPSs with different levels of distributed intelligence. The resulting instantiations illustrate that our RM can model a wide range of CPPSs. Secondly, we demonstrate the RM's practical relevance by modeling a real-world production system from a CPPS model factory.

For our three fictional application scenarios, we assume that a CPPS is responsible for a specific production step (Figure II.1-5) involving a band conveyor with one actor (conveyor drives), a production machine with two actors (robot gripper and laser welding device) and one sensor (temperature).

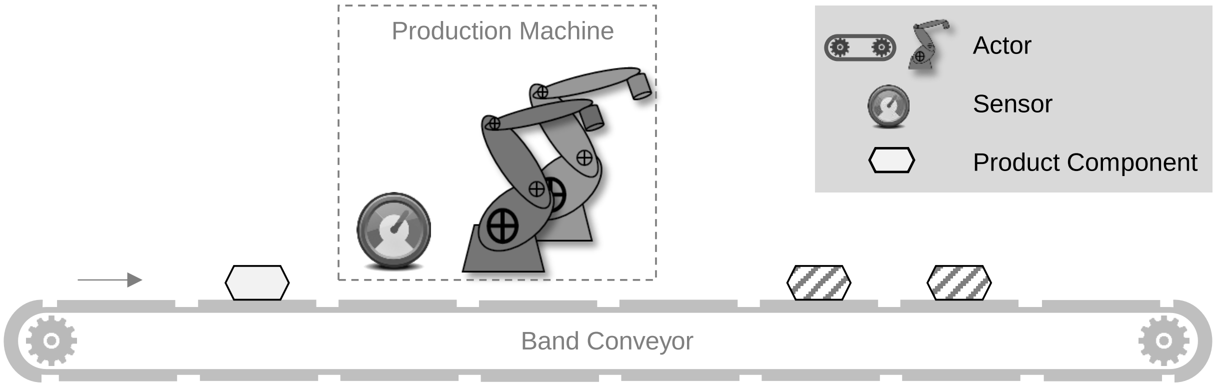

Figure II.1-5: Initial situation for our three exemplary scenarios

Our three exemplary scenarios illustrate different versions of controlled self-organization (i.e., different locations of Organic Components). Note that, in addition to these pure form examples (each of which feature only one type of organic behavior), there can also exist hybrid scenarios.

Within *Scenario 1 (Smart Control Panel),* organic capabilities are centralized in a central control panel with one human operator (Figure II.1-6). In contrast to semi-finished products, the central control panel, the band conveyor, and the production machine are connected to the CPPS Network Infrastructure and are therefore part of the CPPS. XaaS or External System Interfaces are not integrated. The central control panel's communications with Actors and Sensors are indirect, and channeled via the respective Machine Component's operating software (which is part of the respective machine). Both the band conveyor and the production machine feature an additional on/off switch. To avoid repetitions, below we list only the differences between this scenario and the other fictional cases.

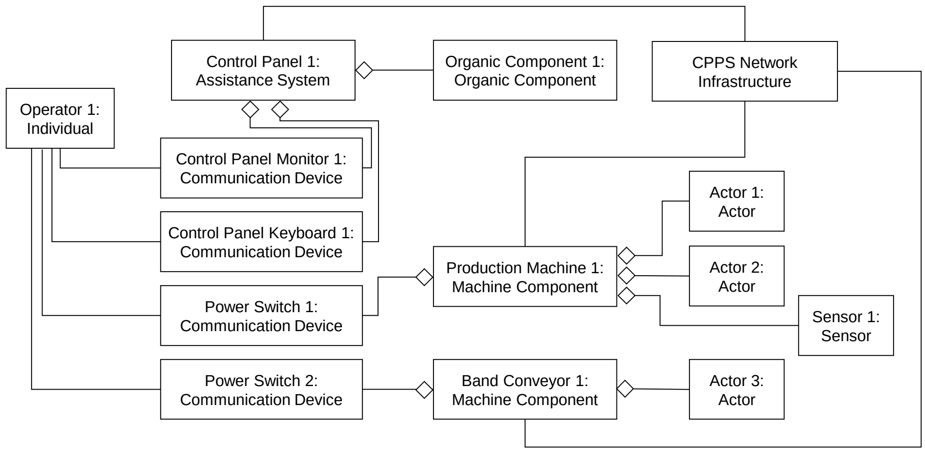

Figure II.1-6: Reference model for "Smart Control Panel" (Scenario 1)

Scenario 2 (Smart Machine Component) differs from the first scenario in that organic capabilities are centralized to the production machine, which is therefore an SO (Figure II.1-7). Moreover, there are two human operators who communicate with the inner system by via two different devices. Operator 1 uses a SmartPad while Operator 2 uses an integrated local control panel (in the production machine), both of which have no organic capabilities. The operators interact with each other as they are part of the same production process. Communication with Actors and Sensors can also be conducted directly through the CPPS Network Infrastructure.

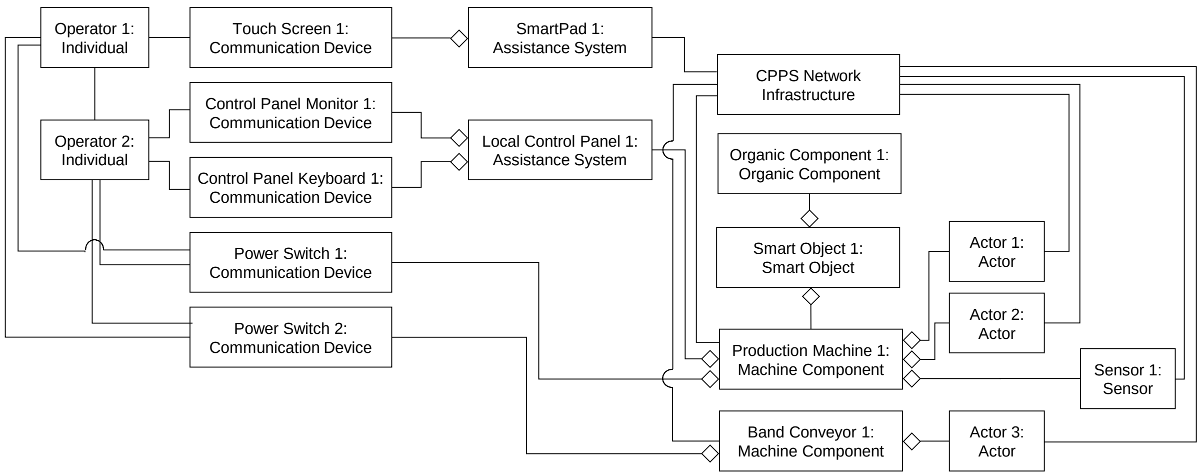

Figure II.1-7: Reference model for "Smart Machine Component" (Scenario 2)

Scenario 3 (Smart Product Components) differs from the first scenario in that organic capabilities are decentralized as part of semi-finished products, which are therefore SOs (Figure II.1-8). More precisely, all SOs possess a virtual twin that is managed by a multi-agent system. The multi-agent system is executed in an external cloud (XaaS). The functions of organic capabilities, however, are located in Product Components. The human operator can set objectives and frame conditions for the SO using a central control panel which does not have organic capabilities. Product Components are part of this CPPS as long as they are connected to the CPPS Network Infrastructure (e.g., as long as they are transported by the CPPS's band conveyor). Within this fictional application scenario, we include three Product Components that are currently part of the CPPS. The virtual twins of these SOs use the CPPS Network Infrastructure to inform the production machine of required production steps. The CPPS possesses an additional External System Interface, which the SOs can use to communicate with subsequent CPPSs regarding their progress in the production process. Again, communication with Actors and Sensors can be conducted directly through the CPPS Network Infrastructure.

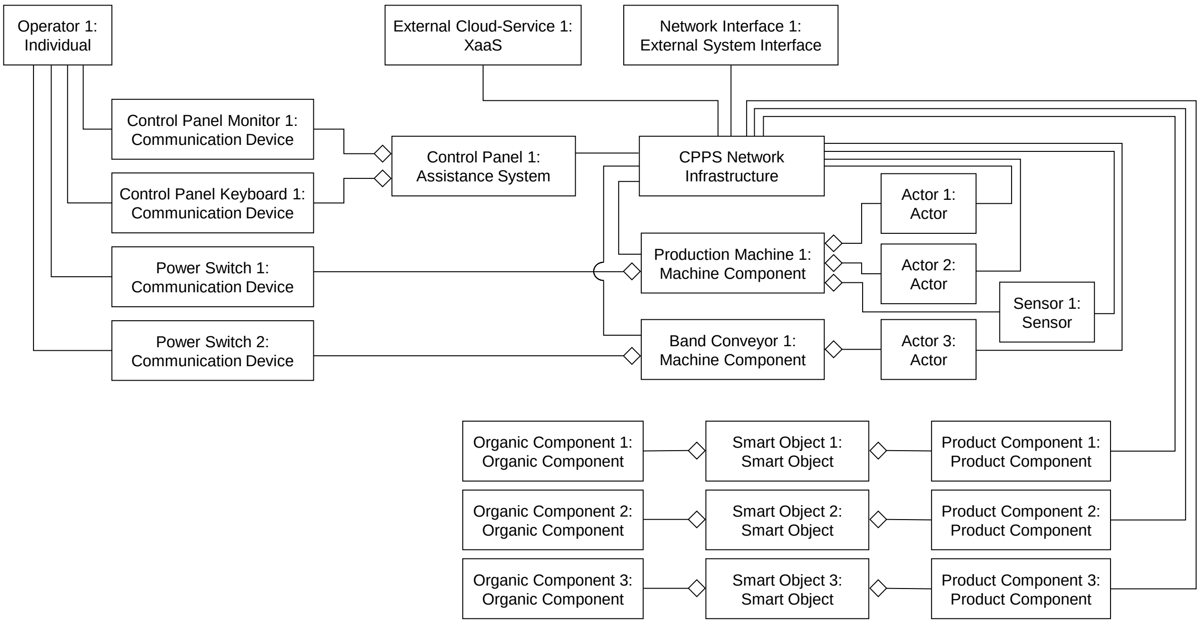

Figure II.1-8: Reference model for "Smart Product Components" (Scenario 3)

To demonstrate the practical relevance of our RM, we use the example of a real-world CPPS from a model factory. More precisely, we model a *smart turning machine* (Figure II.1-9). The turning machine is primarily used to demonstrate the shaping of materials such as plastic or metal, and is currently processing wheel rims. In this case, a work piece (Product Component) is first clamped into the machine and then rapidly turned against a cutting tool. The turning machine can also perform drilling tasks. Various Actors are involved in processing a work piece: The turning machine involves a spindle, to rotate, a clamping device, for fixing work pieces, and a drill, to shape a work piece. It also features a tool turret, for the exchange of different drill types, and a tool arm, which moves the drill with three degrees of freedom.

Work pieces are equipped with RFID tags which hold information on individual manufacturing orders. As the work pieces possess no organic capabilities, these entities are not integral parts of the CPPS. RFID tags are read either by an RFID scanner integrated within the machine or a mobile RFID scanner on the operator's glove. Further Sensors monitor the electrical flow of the turning machine and the gripping force applied to the work pieces (by applying strain gauges). All data is stored in a private cloud located within the model factory. The private cloud runs a manufacturing execution system which possesses organic capabilities, in that the software can observe up to eight subsequent work pieces and then select the appropriate computerized numerical control. The operator can communicate with the inner system in two different ways: s/he can use a local control panel equipped with two monitors, a touch pad, and a keyboard, or s/he can use gesture and voice controlled smart glasses. Thereby, both assistant systems are an integral part of the machine and thus have no direct connection to the CPPS Network Infrastructure. Strategic specifications such as production schedules are predefined through an ERP system, which is connected via an External System Interface. Work pieces are delivered by a logistic robot, which is not part of the CPPS. Future extensions of the smart turning machine are set to include, among other things, an external XaaS, and SOs (smart work pieces) that control logistic robot delivery.

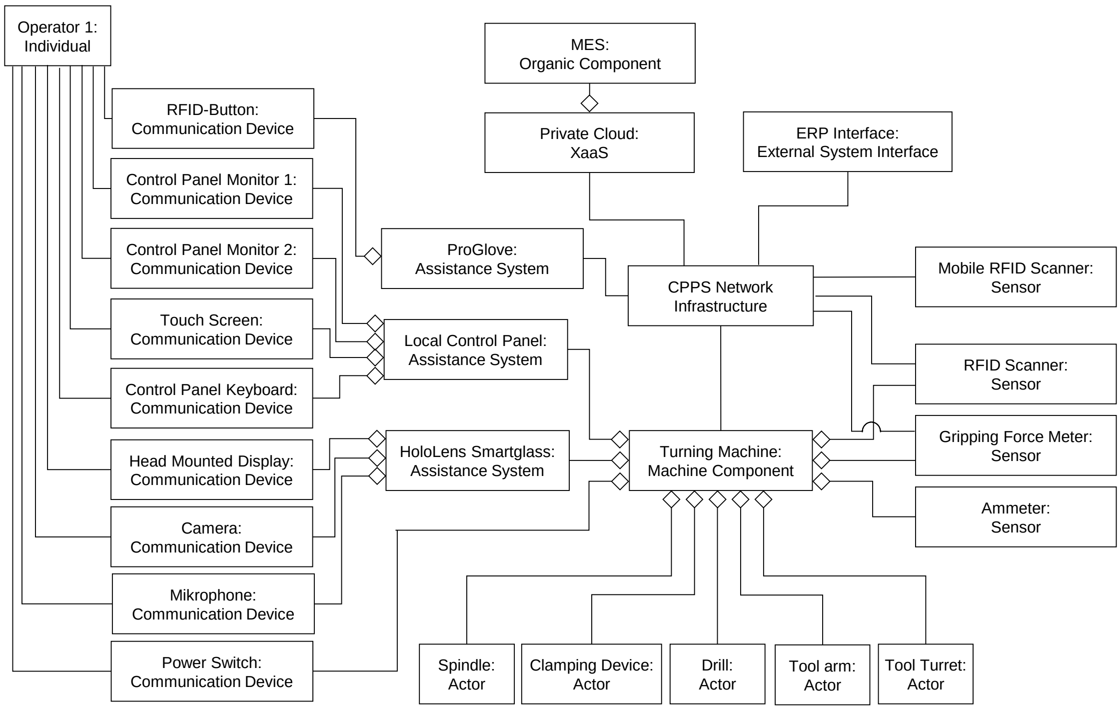

Figure II.1-9: Reference model of a smart turning machine (real-world example)

II.1.7 Discussion

Our theoretically significant and empirically validated artifacts comprise twelve entities structured along five entity dimensions, which we created and evaluated using the iterative development process by Nickerson *et al.* (2013). In order to meet our subjective ending conditions, we required our artifacts to be concise, robust, comprehensive, extendible, and explanatory. These requirements attest to the utility of our artifacts, providing guidance for descriptive evaluations within the development process (Hevner & Chatterjee, 2010, p. 119). Our industry experts and focus group members confirmed the utility of the artifacts in relation to our subjective ending conditions. In addition, although related work exhibits varying numbers of different terms for CPPS entities, and varying levels of abstraction, we can confirm that, to the best of our knowledge, all identified (relevant) entities fall within the scope of our taxonomy (which additionally confirms comprehensiveness, i.e., completeness). If terms are not at the same level of abstraction as our dimensions and entities, they are either more fine-grained than our taxonomy or part of a Local IS Component (cf. Section II.1.4), or they are merely a CPPS application scenario rather than an actual CPPS entity. Following Nickerson *et al.* (2013), we strive “to develop useful taxonomies, but not necessarily ‘best’ or ‘correct’ ones, as these cannot be defined and, in fact, may be moving targets that could change over time” (p. 341). This is in line with Hevner *et al.* (2004), who state that “the search for the best, or optimal, design is often intractable for realistic information systems problems’ (p. 88). However, we can confirm that we used our literature reviews, focus group discussions, expert interviews, and internal discussions to identify and remedy any visible problems.

As the usefulness of an artifact is measured by the number of researchers and practitioners using it (Nickerson *et al.* 2013), we took a first step and applied our RM to three fictional application scenarios and one real-world example. On the one hand, our fictional application scenarios illustrate the wide range of possible instantiations of our RM, which many be used to model a broad variety of different CPPSs. On the other hand, our real-world example demonstrates the artifact’s practical relevance and applicability. However, usefulness will ultimately be proven by other researchers and practitioners using our artifacts, which will be subject to future research. Thereby, our RM can serve as a foundation for the development and implementation of urgently needed CPPS modeling approaches (such as CPPS system architectures), particularly in inter-organizational and interdisciplinary project teams that have not yet jointly defined, classified, and linked the entities of CPPSs. Moreover, our artifacts lay the foundation for future research analyzing the characteristics of CPPSs. As illustrated in Section II.1.2, definitions and classifications of CPPS characteristics currently lack clarity. Therefore, in the next step, future researchers can use our research method to apply similar analysis to CPPS characteristics. A respective taxonomy and RM for CPPS characteristics can then be connected with our taxonomy and RM to create artifacts which further increase a common understanding of CPPSs and support the development of appropriate modeling approaches. This also attests to the extendable nature of our artifacts, in line with Nickerson *et al.* (2013). By modeling on a high level of abstraction, however, our RM refrains from modeling deeper technological details, i.e., it suggests the abstraction of CPPS entities that would be mapped on a deeper (e.g., third) lane of the proposed taxonomy (i.e., different types of Machine Components, Assistance Systems, Sensors, Actors etc.). Hence, we limit our definition of comprehensiveness to the chosen level of abstraction and leave the extension of our artifacts for future research. Increasing CPPS complexity and the consequent need for concise approaches (Nickerson et al. 2013) may necessitate industry-specific specialization in the case of our taxonomy and RM. Moreover, although our RM supports the creation of CPPS modeling approaches, there are further challenges for IS designers which we do not address in this paper (e.g., how to instantiate the use of our RM in huge production facilities, where companies require a clear illustration of a huge number of CPPS entities; how to integrate our RM into existing modeling approaches and simulation software for plant layouts). These are also important directions for future research.

Increasing complexities and dependencies in information networks within and across smart factories are highly relevant to operational risk management, as failure of a single component can develop into a cascade of failures across the whole of a production system. Due to optimized inventory and capacity utilization, and the interdependencies between information networks and physical production processes, such cascade failures have the potential to cause huge economic damage. Therefore, operational risk management must involve an integrated consideration of information and material flows (i.e., value flows), and the possibility of transparently modeling and analyzing these hybrid networks. As we developed our artifacts from an information-driven perspective (i.e., we require all CPPS entities to be either information receivers, transmitters, or both), future research could also model further (non-CPPS) entities of physical value creation (e.g., auxiliary material and non-intelligent product components) and the relations between material flows. Taxonomies and RMs for such hybrid networks may be useful for risk identification and evaluation, as they enable the modeling of a system’s robustness in the case of different failure scenarios, and can therefore be used to estimate the potential loss of value creation in the case of specific risk events. This enables significant economic investment decisions, and the prioritization of preventive and curative countermeasures (e.g., early-warning systems, redundant CPPS entities, or fast diagnosis systems).

II.1.8 Conclusion

Researchers and practitioners attribute significant potential to the emerging field of CPPSs, the development of which has been accelerated by the digital transformation. However, academic knowledge and practical implementations are still at an early stage. Due to a lack of a common understanding of CPPSs, existing literature offers no consensus regarding entities and characteristics of CPPSs. This is an obstacle to the development of modeling approaches, which are urgently needed in order to make the complexity and structural opacity of CPPS more manageable. Applying the iterative development process by Nickerson *et al.* (2013), we created and evaluated a terminology, a taxonomy, and an RM for defining and classifying CPPS entities and illustrating their interrelations. To demonstrate the efficacy and general applicability of our artifacts, we applied our RM to three fictional application scenarios of CPPSs with differing levels of distributed intelligence, and to a real-world production system of a CPPS model factory. The proposed artifacts are subject to further limitations: On the one hand, because we did not take a structured, state-of-the-art approach to the CPPS literature, we cannot exclude the possibility of further model extensions. As our literature reviews, focus group discussions, expert interviews, and internal discussions did not yield any further evidence, we claim that our artifacts are comprehensive. On the other hand, because we take a functional approach to CPPS technology, we do not attempt to address the economic aspects of CPPSs, such as necessary investments, costs, respective risks, amortization periods, or other aspects such as the suitability of CPPS technology for specific applications. When it comes to CPPS investment decisions, methods enabling the economic evaluation of certain CPPS designs in different application scenarios and companies are required.

Despite these limitations, our artifacts represent an important step towards the establishment of a common understanding of the IoT application area of CPPSs. In particular, we encourage other researchers and practitioners to join our interdisciplinary endeavor to enable future CPPS applications and modeling approaches which make the complexity and structural opacity of CPPS more manageable.

II.1.9 References

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II.1.10 Appendix

Details on our evaluation iterations

<table>
<tr><th>Loop</th><th>Description</th></tr>
<tr><td rowspan="3">1</td><td>We began the initial evaluation loop with our first focus group meeting. The meeting involved a discussion about our motivations for the study, the results of our literature review, and the first draft of our artifacts. Below, we list select changes and annotations:</td></tr>
<tr><td>Key Changes:
• Our initial plan was to create a broad-ranging taxonomy which included information about CPPS entities and characteristics. However, in order to ensure we did not spread ourselves too thin, we decided to narrow our focus and concentrate on CPPS entities and their relations. CPPS characteristics should be addressed by future research. We also limited the proposed RM to a generic representation of entities, i.e., we excluded the middle and lower compartments of the class containers.
• We chose to include aggregations in the RM – i.e., we chose to allow the modeling of “whole-part” relations – as, in some cases, these entity relations are more appropriate. This is useful because some CPPS entities we identified are integrated in other CPPS entities.</td></tr>
<tr><td>Key Annotations:
• The focus group confirmed the general relevance of our research objective. They also approved of our decision to use the iterative development method by Nickerson et al. (2013).
• The focus group supported our intention to use semi structured interviews with the industry experts, as this interview method allows for a more open conversation and broader feedback than structured interviews.</td></tr>
<tr><td>2</td><td>The second evaluation loop consisted of two (separate) interviews with industry experts, and a subsequent discussion with our focus group. Our first interview partner (IP1) works for one of the global market leaders in robotics. The company</td></tr>
</table>

	focuses on the automation of production processes, combining all three domains of CPPSs. IP1 is the company's Head of IT Project Planning, and is directly engaged with the CIO of the company. Our second interview partner (IP2) works as Head of IT-Infrastructure for a globally-established technology company. The company's products and services are primarily used for information management such as IT components, networks, and communication. IP2's involvement serves our need to evaluate the Cyber Components of the proposed models. The second evaluation loop yielded the following select changes and annotations:
	Key Changes: • On the advice of both industry experts and focus group members, we limited the proposed taxonomy to the use of two lanes (i.e., entity dimensions and entities). This was done in order to ensure that the taxonomy was comprehensive and readable, and to establish a consistent depth of branching (the first draft of our taxonomy included a third lane of CPPS entities; however, this did not extend to all branches in the hierarchical structure). We also limited the proposed RM to the representation of those two lanes. • IP2 noted that a previous Cyber Component, "Cloud Data Storage", could be overly restrictive because IT services can exceed the scope of IaaS. Therefore, we created the more comprehensive XaaS Component, which we validated within our focus group discussion. • IP1 questioned our definition of the CPPS Network Infrastructure and recommended that we describe this entity in more detail. In particular, IP1 asked about CPPS system boundaries and the possibilities of geographically distributed production within a single CPPS. We revised our description of this entity to include more aspects. • IP1 and IP2 both emphasized that some exemplary instantiations of the proposed RM would improve clarity for practitioners and demonstrate applicability. Therefore, we created three fictional application scenarios involving different possibilities for controlled self-organization. Our focus group confirmed that these examples were clear and relevant.

	• Following our focus group discussion, we chose to combine different CPPS entities in the dimension Human Being (we had originally distinguished between "Business", "Operations", "Engineering", "Maintenance", and "Training") in order to achieve the same level of abstraction as in other CPPS entities, such as Machine Components. Secondly, we chose to remove the introduced Local IS Component (see Section II.1.4.2.2 for details). Finally, we renamed the former Cyber Component "Intelligent Component" as "Organic Component", and elaborated its particular type of intelligence.
	Key Annotations: • IP1 and IP2 both confirmed ongoing technological development to be the key driver of progressive CPPS adaption. More precisely, they mentioned that computing power and data storage are no longer limiting factors in the implementation of CPPSs thanks to continuous ongoing reductions in the prices of CPU and RAM. However, new challenges in information management continue to arise as system complexity increases along with the number of nodes in a network. Depending on the form of information management (distributed or central), the degree of opacity increases. The topic of Big Data was also discussed, as the growing number of Sensors in CPPSs raises the question of how to usefully analyze the increasing amount of data. • IP1 stated that the taxonomy contributes to a common understanding, and that they would be interested in applying the final RM in parts of their own production facility. In particular, IP1 highlighted the value of creating transparency. A project manager has multiple points of contact with other corporate areas and responsibilities, meaning that a common base of understanding is a factor critical to success. • IP2 emphasized that the taxonomy and the RM can provide information on different levels of abstraction regarding the system's design. IP2 also emphasized that enterprise architecture management requires appropriate tools to map the resulting system design, particularly during production planning phases. To date, there exist no suitable tools which support the modeling of complex CPPS architectures. According to IP2, the majority of companies

<table>
<tr><td></td><td>continue to reference computer-aided technologies (CAx), or even gather the desired information from visual programs such as PowerPoint (cf. Zuehlke 2010). However, these tools can only insufficiently depict relations between entities within and between complex systems, which is even more critical for CPPSs as systems of systems.

• IP1 and IP2 both agreed to a second interview in a later stage of development.</td></tr>
<tr><td rowspan="2">3</td><td>The third evaluation loop consisted of four (separate) interviews with industry experts and a subsequent discussion with our focus group. IP3 works for one of the world market leaders in fixing technology. Because the company is not only developing, but also globally manufacturing and distributing its products, it faces the challenge of digitizing and networking its production processes. IP3 is, among other roles, Head of Supply Chain Management and Product Data Management. IP4 works for an international automotive manufacturer and is responsible for IT Enterprise Architecture Management in Production Control and Maintenance. IP5 and IP6 work for an IT service provider that specializes in conducting IT transformation projects for customers in several industries (e.g., automotive, logistics, telecommunications). As Managing Consultants, IP5 and IP6 are currently supervising a large IT transformation project. IP5 manages inter-divisional strategic planning tasks, whereas IP6 (as an IT architect) focuses on the technical design, modification, and implementation of the targeted IT system and infrastructure. The third evaluation loop yielded the following select changes and annotations:</td></tr>
<tr><td>Key Changes:

• IP3 stated that, at first glance, the majority of the presented CPPS entities were intuitive. The exceptions to this were the Organic Components and SOs, which (therefore) required a careful explanation. However, IP3 confirmed that the existence of both CPPS entities was justified. After reviewing the respective descriptions, we specifically improved the section outlining our motivation for including our Organic Components.

• IP4 suggested adding an aggregation between Product Components and Actors. Because the proposed RM allows for Product Components as SOs, it is conceivable that corresponding virtual twins temporarily possess full access to</td></tr>
</table>

	actors, which would make the latter, from a functional point of view, part of the respective SO. We accepted this advice and added the respective aggregation. • IP4 suggested sharpening the definition of the CPPS Network Infrastructure in order to clarify that this CPPS entity does not necessarily implicate one central network node; rather it can also include several distributed network nodes which may or may not be connected to one another. Hence, we added a corresponding explanation. We were also asked to ensure that the dimensions of Bridging and Physical Production Components were sufficiently demarcated. In response, we reviewed our dimension descriptions and added minor improvements. • IP5 noted that Sensors and Actors can not only exist as integrated elements of specific Physical Production Components, but also as independent versatile tools for common monitoring and control tasks. Following IP5's recommendation for direct network communication, we added an association between the CPPS Network Infrastructure and Sensors and Actors. • The focus group discussion endorsed: (1) the changes based on our interviews with IP3, IP4, and IP5, and (2) one further change made by the authors: we deleted an association between Organic Components and the CPPS Network Infrastructure and added an association between Assistance Systems and the CPPS Network Infrastructure. This is reasonable because we regard an Organic Component to always be part of other CPPS entities, which should (therefore) possess networking capabilities. Further, an Assistance System does not necessarily integrate Organic Capabilities (for example, if the Assistance System is functionally limited to the interpretation and transmission of human control input; please cf. our fictional application scenarios 2 and 3).
	Key Annotations: • IP3 and IP4 both found the proposed approach to be abstract yet suitable for a combined top-down and bottom-up approach. After applying the proposed RM to a special CPPS application scenario (production environment), practitioners can subsequently map their basic CPPS entities to the generic objects. • IP5 stated that self-organizing systems such as CPPSs already exist in areas of distribution and logistics. Traditional industries, however, lag some distance

<table>
<tr><td></td><td>behind this technological progress. Therefore, IP5 considered an RM for CPPSs to be a valuable means to reduce this gap.
• IP6 emphasized that the taxonomy and RM should predominantly include entities that deliver new insights to CPPSs. Therefore, IP6 confirmed the valid omission of the Local IS entity for pervasive IS, i.e., local hardware (e.g., local data storage) and software components (e.g., common operating software). He also confirmed that the general description of our Organic Component is suitable to describe a wide range of CPPSs with different levels of intelligent behavior and self-control.
• IP3, IP4, IP5, and IP6 confirmed that, to the best of their knowledge (and after integrating their respective feedback), the proposed artifacts are concise, robust, comprehensive, extendible, and explanatory. Further, they confirmed the general relevance of our research questions, and that the proposed taxonomy and RM could be a useful tool for their field of work. All experts confirmed our examples to be expedient.</td></tr>
<tr><td rowspan="2">4</td><td>The fourth evaluation loop consisted of three final expert interviews with a new expert, IP7, and the previous interviewees IP1 and IP2. IP7 works as Principal of Digital Transformation for a medium-sized automotive supplier. Because we had made some changes to our model following our first interviews with IP1 and IP2, we asked both experts for a second meeting.</td></tr>
<tr><td>Key Changes:
• IP7 recommended extending the description of our XaaS entity in order to clarify that this component does not only imply external services but also private on-premises solutions. This is reasonable because “service” may also refer to internal services and, therefore, may include a company’s central server system and centrally hosted application software. We accepted this suggestion and improved our XaaS description.
• IP1 had a final suggestion for the XaaS Component (which had not existed during our first interview). Because we allow this component to exhibit SaaS capabilities, the proposed RM should allow XaaS to possess organic capabilities. For example, organic manufacturing execution systems with observe and control capabilities may be operated by external or internal cloud</td></tr>
</table>

	services. We accepted this suggestion and added an aggregation between XaaS and Organic Components.
	Key Annotations: • IP7 noted that transparency of the cyber-physical production environment is one of their current core issues. In this context, he explicitly emphasized the potential of the proposed RM. However, he also indicated that the transformation of the proposed taxonomy and RM into application software for IS designers will involve challenges. These include the modeling of enormous and complex production facilities for which companies require a clear presentation of the instantiated RM and the implementation of functions to model individual CPPS sub-entities (because our approach is generic and limited to two lanes within the proposed taxonomy). We added this annotation to our limitations. • IP1 and IP2 stated, independently of one another, that our RM had made significant progress. • IP7, IP1, and IP2 confirmed that, to the best of their knowledge, the proposed artifacts are concise, robust, comprehensive, extendible, and explanatory. Further, they confirmed the general relevance of our research questions, and that the proposed taxonomy and RM could be a useful tool in their field of work. All experts confirmed that our examples are expedient.

Table II.1-2: Details on our evaluation iterations

II.2 Research Paper 2: "Scheduling Flexible Demand in Cloud Computing Spot Markets - A Real Options Approach"

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Published in:	Business & Information Systems Engineering, 62(1), 25-39

Abstract:

The rapid standardization and specialization of cloud computing services have led to the development of cloud spot markets on which cloud service providers and customers can trade in near real-time. Frequent changes in demand and supply give rise to spot prices that vary throughout the day. Cloud customers often have temporal flexibility to execute their jobs before a specific deadline. In this paper, the authors apply real options analysis (ROA), which is an established valuation method designed to capture the flexibility of action under uncertainty. They adapt and compare multiple discrete-time approaches that enable cloud customers to quantify and exploit the monetary value of their short-term temporal flexibility. The paper contributes to the field by guaranteeing cloud job execution of variable-time requests in a single cloud spot market, whereas existing multi-market strategies may not fulfill requests when outbid. In a broad simulation of scenarios for the use of Amazon EC2 spot instances, the developed approaches exploit the existing savings potential up to 40 percent – a considerable extent. Moreover, the results demonstrate that ROA, which explicitly considers time-of-day-specific spot price patterns, outperforms traditional option pricing models and expectation optimization.

II.2.1 Introduction

With cloud services' continuously increasing usage and business relevance, their market is becoming increasingly solvent (Keller and König 2014). At the same time, standardization is increasing. This development has allowed users to dynamically adapt their cloud services demand from no to nearly unlimited resources (Mell and Grance 2011). In a rather recent move, Infrastructure-as-a-Service (IaaS) providers, such as *Amazon Web Services* (AWS), reflect the varying demand patterns by offering their services at fluctuating *spot prices* (Karunakaran and Sundarraj 2015), which are volatile throughout the day (Ben-Yehuda et al. 2013). This way, such providers seek constant server utilization to avoid idle capacity and large peaks.

In many use cases, customers require the instant delivery of cloud services. Nevertheless, customers may defer jobs, for instance, simulations, rendering jobs, and scientific computations. Whenever customers do not require a cloud service instantly and expect the spot prices to fall, they can defer their demand in order to realize cost savings. The time they are willing to wait for their computing job opens a window of temporal flexibility.

Evaluating the cost savings potential of a customer's window of temporal flexibility is a complex task, since cloud spot prices may change frequently, as we will illustrate. Consequently, cloud customers require strategies that take the tradeoff between the costs and the waiting time into consideration (Karunakaran and Sundarraj 2015; Tang et al. 2012). Furthermore, cloud customers may not even be aware of their temporal flexibility. We identify two main obstacles to utilizing temporal flexibility in cloud computing spot markets: First, decision support for customers requires near real-time analytics on when and how long to defer computing jobs given the uncertain price development. Adequate IS or web services are required to help exploit the existing savings potential optimally. Second, deferring jobs requires customers to change their demand behavior, which might inconvenience them. Applying such IS or web services could also incur costs for process implementation and additional planning, while waiting for jobs could lead to opportunity costs. However, such costs are highly dependent on customers' individual circumstances: the extent of their cloud services dependency, IS infrastructure, employee training, etc. We consequently focus on evaluating objectively measurable savings, because cloud customers need an estimation of their flexibility's current value to weigh it against the incurred expenses.

To address both obstacles, we apply real options analysis (ROA), which other IS research domains have established as a valuation method designed to capture the flexibility of action under uncertainty (Amram and Kulatilaka 1999; Benaroch and Kauffman 1999; Trigeorgis and Sick 1996). We model a customer's temporal flexibility as a deferral option. This real option serves to determine a value for the right to act or to await another opportunity over a period. From this overarching research objective, we derive our research question:

'How can cloud services customers quantify and exploit their demand flexibility's monetary value by using real options analysis and given uncertain short-term price development?'

To address our research question, we adapt and apply multiple option pricing models and process a dataset of Amazon *Elastic Compute Cloud* (EC2) spot prices. Our research objective covers a relevant real-world problem, as cloud customers could profit from decision support for when to purchase cloud services within a temporal flexibility window to optimally exploit their savings potential. Under market principles, such times of day would have lower cloud service demand than the server capacity available. Shifting jobs to these times contributes to balancing the cloud service demand and the supply.

We structure the remainder of this paper as follows: in Section II.2.2, we present related work on cloud computing markets and ROA. In Section II.2.3, we analyze our dataset of EC2 spot prices. In Section II.2.4, we adapt multiple approaches to quantify and exploit the monetary value of short-term temporal flexibility in cloud computing demand. We thereafter evaluate these approaches in a historical simulation and sensitivity analysis in Section II.2.5. Finally, we discuss the results in Section II.2.6 and conclude the paper in Section II.2.7.

II.2.2 Cloud Computing Markets and Real Options Analysis

II.2.2.1 Current Developments in Cloud Computing Markets

Cloud computing with its pay-as-you-go model and flexible, on-demand resource allocation comprises three major product categories: namely IaaS, Platform as a Service (PaaS), and Software as a Service (SaaS) (Mell and Grance 2011). Keller and König (2014, p. 4) identify three recent trends in cloud computing that "are likely to transform the current cloud landscape":

- increasing standardization, especially viable in IaaS
- increasing SaaS specialization for particular user groups, such as private users or specific industries

- increasing actor dependencies.

These developments specifically occur in emerging cloud marketplaces (Keller and König 2014). Major cloud providers offer standardized products, such as virtual machines with a given operating system, CPU, RAM, and storage. However, especially in the IaaS context, the standardization of cloud computing fosters an oligopolistic market structure, in which the largest two providers (AWS and Microsoft) provide the deployment environment of about 70% of the current applications (Skyhigh Networks 2017). These companies profit from enormous economies of scale, which might, however, stall innovation and progress in the cloud market (Bestavros and Krieger 2014). Nevertheless, recent attempts, such as the Deutsche Börse Cloud Exchange, the Cloud Commodities Exchange Group, and the Massachusetts Open Cloud Exchange, have opened the IaaS markets to smaller providers, thus increasing the market dynamics. Moreover, standardized application programming interfaces (API), which tools like Swagger or CloudStack use, enable the dynamic exchange of commoditized SaaS services, such as weather services (Lewis 2013; Loutas et al. 2011a; Loutas et al. 2011b).

II.2.2.2 Cloud Computing Spot Prices

In cloud computing, AWS first introduced spot prices for their computing service Amazon EC2 in 2009. AWS operates EC2 spot instances in 14 locations with about 40 products (Amazon Web Services 2017), which can substitute one another. As AWS' excess capacity, EC2 spot instances are normally cheaper than regular on-demand instances based on a fixed price (Kamiński and Szufel 2015). Similar to spot markets for stocks, electricity, and commodities, a market mechanism brings together demand (bids) and supply (offers) in a Vickrey auction to form EC2 spot prices (Cheng et al. 2016). However, AWS applies a hidden reserve price algorithm to artificially generate a linear dependency between the availability and the spot price that is consistent over multiple instance types and locations (Ben-Yehuda et al. 2013).

Currently, there are different research streams on cloud spot prices. One research stream applies reverse engineering for a better understanding of EC2 spot instances and to deconstruct AWS' spot pricing mechanism (e.g., Ben-Yehuda et al. 2013; Li et al. 2016a). These papers do not provide decision support algorithms. As prices differ between regions, a second research stream analyzes customer strategies to reduce costs by spatially distributing the use of spot instances (e.g., Cheng et al. 2016; Marathe et al. 2014). Since our objective is to study temporal instead of spatial flexibility, we are more closely related to a third research stream focusing on spot price prediction. For example, Baughman et al. (2018) propose a model to predict EC2 spot prices based on long/short-term memory recurrent neural networks. Khandelwal et al. (2017) propose a model based on random forest regression for predicting EC2 spot prices one day and one week ahead. These scholars demonstrate that their non-parametric machine learning approach outperforms previous approaches based on support vector machines (Arevalos et al. 2016) and artificial neural networks (Wallace et al. 2013). Cai et al. (2018) criticize several existing models for being static and neglecting the correlation of sequential cloud spot prices. Instead, these authors propose two Markov regime-switching autoregression models and one autoregressive integrated moving average model that integrate new observable information dynamically to adjust price predictions. These examples are just an excerpt from an extensive research stream, which is, nevertheless, inappropriate for our purposes. Although these studies present sophisticated models for spot price prediction based on (auto)regression and machine learning, their point estimators provide only limited decision support, as they do not consider the type of customer service request and the relevant optimization restrictions.

Vieira et al. (2015, p. 498) distinguish three categories of service requests: “fixed-time requests” without temporal flexibility (e.g., continuous monitoring tasks or websites), “floating-time requests” which can be interrupted and are temporally flexible, and “variable-time requests” which cannot be interrupted, but are temporally flexible. As we aim to quantify and exploit cloud customers’ (short-term) temporal flexibility, we will not further consider fixed-time requests.

Research not only provides spot price predictions, but also decision support in terms of bidding strategies for floating-time and variable-time requests. Floating-time requests require cloud customers to apply complex check-pointing mechanisms and snapshots. Andrzejak et al. (2010) present a probabilistic model that employs temporal flexibility to optimize bidding strategies. By focusing on cost-reliability trade-offs and the selection of instance types, they conclude that cost savings negatively affect execution time (and vice versa) and that switching from standard or high-memory to high-CPU instance types can save costs. Tang et al. (2012) and Tang et al. (2014) advance this approach by formulating a constrained Markov decision process based on linear programming. These authors improve Andrzejak et al.’s (2010) approach in terms of cost savings and execution time. In these three papers, the researchers set a price threshold and maximize the reliability of long-dated computations (2.6 to 22.6 hours) over a timeframe of several days. Zafer et al. (2012) extend these approaches by proposing a dynamic bidding strategy for floating-time requests with a specific deadline. While their suggested bidding strategy favors the use of EC2 spot instances due to their lower costs, it can only guarantee that jobs will be executed by a fixed deadline if it also uses EC2 on-demand instances.

We aim to contribute to the research of variable-time requests that must not be interrupted, such as MapReduce jobs (Dadashov et al. 2014) and other highly parallelized jobs (Kumar et al. 2018). Distributed analytics jobs, for example, those using Hadoop or Spark, are particularly suitable for variable-time requests (Kumar et al. 2018). Zheng et al. (2015) and Tamrakar et al. (2017) analyze the execution of MapReduce jobs, with the former concluding that using spot instances from different markets can reduce costs by 93% compared to regular on-demand cloud instances, but can also increase computation time by 15%. Zheng et al. (2015) and Zafer et al. (2012) model a fixed deadline, but can only guarantee this by using additional EC2 on-demand instances. In terms of the spot markets, they try to balance the trade-off between the costs and the reliability of the job execution.

Extending all previous literature on the topic, we contribute an approach that guarantees to execute variable-time requests in spot markets within a customer's temporal flexibility window. We design the approach to be easier to understand and implement than other approaches, because we reduce the decision complexity to "when to bid" (ignoring "how much to bid") by considering the expected spot price development. We focus on one instance type on one cloud spot market. In contrast to existing literature, we implicitly assume that a customer's bid is high enough for the job execution to be uninterruptible. This assumption is valid for Vickrey auctions, in which a bidder at most pays the common spot price instead of the bid. Our initial motivation also requires our approach to evaluate short-term temporal flexibility while explicitly considering uncertainty. We have therefore chosen to apply ROA, which explicitly suits this requirement (Kleinert and Stich 2010). Undertaking ROA requires the available distribution of possible future spot prices; we therefore need to model spot price development as a stochastic process instead of applying regression models that yield point estimators.

II.2.2.3 Real Options Analysis in Information Systems Research

ROA originated from financial option valuation with the aim to evaluate managerial action flexibility that takes uncertainty into consideration. Myers (1977, p. 163) introduced the term *real options* as “opportunities to purchase real assets on possible favorable terms.” Real options comprise “discretionary decisions or rights, with no obligation, to acquire or exchange an asset for a specified alternative price” (Trigeorgis and Sick 1996, p. xi). IS researchers started applying ROA in the 1990s in order to evaluate managerial flexibility in information technology (IT) investments (Ullrich 2013). Benaroch and Kauffman (1999), for example, study the application of discrete-time and continuous-time option pricing models for evaluating investments in IT infrastructure, emerging technology, application design prototyping, and technology-as-products. These scholars conclude that managers can apply traditional option pricing models to non-traded IT assets without loss of validity. Subsequently, Benaroch and Kauffman (2000) examine a case in order to validate the added value of deferral options for strategic IT investments and elaborate on ROA’s advantages instead of traditional IT investment evaluation methods. ROA’s application in IS research focuses mainly on IT investment decisions in general (Chen et al. 2009) or on specific technologies (Lee and Lee 2011; Nwankpa et al. 2016; Wu et al. 2009; Zimmermann et al. 2016).

In our targeted cloud computing research domain, authors apply ROA to migration decisions (Naldi and Mastroeni 2016; Yam et al. 2011), the extension of cloud resources (Alzaghoul and Bahsoon 2013), investment deferral (Alzaghoul and Bahsoon 2014), termination management (Jede and Teuteberg 2016), and risk management regarding cloud services’ availability (Allenotor and Thulasiram 2014). Compared to traditional IT investments, infrastructure services in cloud computing are more separable, meeting the ROA requirement of “complete markets” better (Ullrich 2013, p. 335). In line with the development of cloud exchanges, Meinl and Neumann (2009) propose establishing a contract market to enable grid and cloud services’ customers and providers to trade real options to reserve resources in advance. Náplava (2016) uses ROA to evaluate external IaaS’s additional flexibility compared to that of on-premise solutions. Klaus et al. (2014) develop a model for service providers that evaluates an option to shift excess demand for (e.g., cloud) services to external vendors. This approach determines the business value of shifting flexibility, which decision makers can subsequently use to justify investments in required IS infrastructure.

Our literature review demonstrates ROA applications in IT project and cloud computing business cases. To the best of our knowledge, ROA has not yet been applied to support a cloud service purchase by means of variable-time requests. Kumar et al.'s (2018) research taxonomy of bidding strategy design for cloud spot markets does not list ROA as an already researched method, thus confirming our observation.

Nonetheless, we can build on ROA from other domains. Fridgen et al. (2016) study intraday load-shifting flexibility in the electricity spot market context. These authors propose an ROA-based algorithm to utilize temporal flexibility, adapting and applying the Cox et al. (1979) binomial tree model for discrete-time option valuation. Similar to our approach, they model temporal flexibility as a deferral option: Although purchase before a specified deadline is obligatory, this option gives customers the flexibility to decide on their purchase time in order to exploit the cost savings potential of volatile market prices. Although we adapt their model in some respects, we apply, evaluate, and compare multiple discrete-time approaches to ROA in the light of our research question.

II.2.3 Cloud Spot Market Data Analysis

We base our study on a time series of Amazon EC2 spot market data, which comprises prices and the associated price changes. Encompassing two years of cloud spot market operation, the data span the period January 1, 2015 to December 30, 2016. We acknowledge Spot Price Archive (Javadi et al. 2011), which downloaded a large dataset ranging from January 2009 to December 2016 via the Amazon EC2 API, as the source of this series of spot prices. More precisely, we analyze historical data from the EC2 spot instance "m1.xlarge" hosted in a North Virginia data center ("us-east-1" region). This type of cloud service encompasses four virtual cores, 15 gigabytes of RAM, 350 gigabytes of hard-disk space, and high network performance (Amazon Web Services 2017).

In Figure II.2-1, we provide an example of the hourly statistics of historical 2016 data.

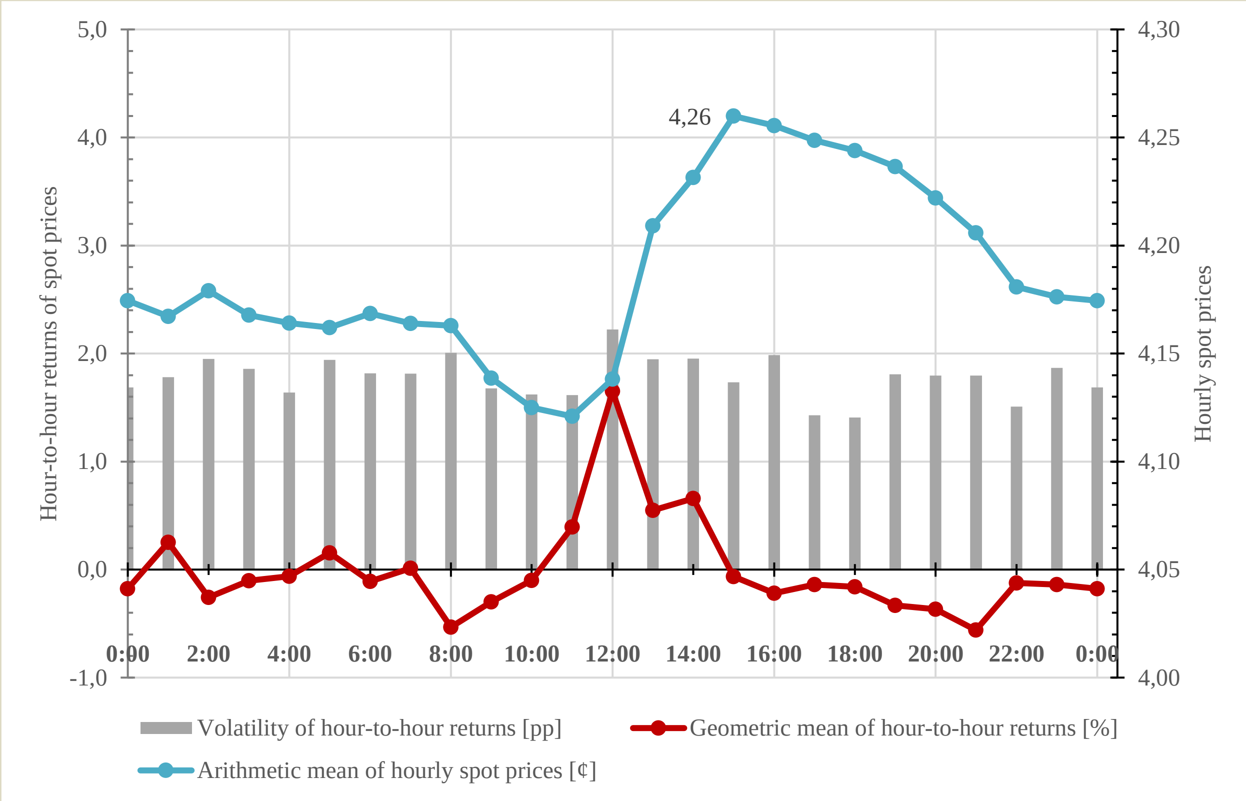


Figure II.2-1: Hourly Statistics of Amazon EC2 Spot Prices

In formulae, we denote references to averaged historical input with a circumflex (^) and the cloud spot price at a given time of day t with $\mathrm{S(t)}$. We compute the historical mean cloud spot price $\hat{\mathrm{S}}(\mathrm{t})$ at time t:

$$\hat{\mathrm{S}}(\mathrm{t}) = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{S(t)_i}}{\mathrm{n}} \tag{1}$$

More precisely, $\hat{\mathrm{S}}(\mathrm{t})$ is the *arithmetic mean* of n historically observed prices at the time of day t. Further, $\mathrm{R(t)}$ is the spot price change, or *return*, from t to $\mathrm{t}+1$, which we express relatively:

$$\mathrm{R(t)} = \frac{\mathrm{S(t+1)}}{\mathrm{S(t)}} - 1 \tag{2}$$

We compute the historical mean return $\widehat{\mathrm{R}}(\mathrm{t})$ from n historically observed cloud spot returns:

$$\widehat{\mathrm{R}}(\mathrm{t}) = \left((1+\mathrm{R(t)_1}) * (1+\mathrm{R(t)_2}) * \ldots * (1+\mathrm{R(t)_n})\right)^{\frac{1}{\mathrm{n}}} - 1 \tag{3}$$

Because single returns may be interdependent growth factors, we choose a *geometric mean* over an arithmetic mean, which could yield false results in this case. More precisely, if spot prices at a specific time of day follow a positive or negative growth trend (increase or decrease, on average, over some days, weeks, or months), applying an arithmetic mean of historical returns to forecast spot prices is likely to overestimate the expected developments, especially regarding more than one estimation period (Amenc and Le Sourd 2003).

In continuation, $\widehat{\sigma}(t)$ is the historical standard deviation, or *volatility*, of cloud spot returns. We compute $\widehat{\sigma}(t)$ as the geometric standard deviation:

$$\widehat{\sigma}(t) = e^{\sqrt{\frac{1}{n} * \sum_{i=1}^{n} \left(\ln \left(\frac{1+R(t)_i}{1+\widehat{R}(t)} \right) \right)^2}} \tag{4}$$

Figure II.2-1 indicates that EC2 cloud spot prices for a reference timespan of 24 months are subject to time-of-day-specific patterns of mean prices, mean returns, and return volatilities. We therefore examine the following hypothesis:

Hypothesis 1: One should extend traditional ROA approaches with time-of-day-specific spot price patterns to optimally exploit the monetary value of short-term temporal flexibility in cloud computing demand.

We test Hypothesis 1 by comparing ROA approaches with and without consideration of time-of-day-specific spot price patterns. Moreover, we verify our modeling decision to apply ROA by examining the following hypothesis:

Hypothesis 2: One should not only model the time-of-day-specific mean prices (or returns), but also the return volatilities to optimally exploit the monetary value of short-term temporal flexibility in cloud computing demand.

We test Hypothesis 2 by applying naive expectation optimization as an alternative to ROA. In the following section, we introduce the respective models. Thereafter we evaluate the models on historical EC2 spot market data.

II.2.4 Model Development

II.2.4.1 Discrete-Time Spot Price Modeling

In this section, we present multiple approaches to support decisions to utilize temporal flexibility in cloud spot markets. We assume a situation in which a customer is temporally flexible (e.g., for some hours) and aims for the lowest possible price in this time window. However, an individual deadline indicating the time at which the customer requires the cloud services at the latest, limits temporal flexibility. Hence, the customer's decision problem is, given the deadline, to defer demand up to the (ex-ante) optimal (cost-minimal) point in time.

Employing ROA, we can model customers' temporal flexibility to defer cloud demand as a deferral option, because they can sell their right to instantly purchase cloud services. This deferral option's value depends specifically on cloud spot prices' (the option's *underlying*) stochastic development and the customer's deadline at which purchase would be obligatory. The deferral option expires right before the given deadline. The customer may exercise the option (i.e., purchase cloud services) only once at an arbitrary decision point in time. The deferral option is therefore similar to an American call option in capital markets.

Assumption 1: Until the deferral option expires, a customer can decide in discrete time increments of equal length whether to exercise the option or not.

In Assumption 1, we limit the decision points in time to a finite and equally distributed number for simplicity's sake. Although approaches that allow continuous-time option pricing and decision making (e.g., Black and Scholes 1973) offer more freedom of action, which would make them preferable, they are rather complex. In particular, there are as yet no closed-form solutions for the continuous-time pricing of American call options under consideration of time-of-day-specific mean prices, returns, and return volatilities. Instead, we research discrete-time approaches that are simple, yet accurate enough to considerably exploit a temporally flexible customer's savings potential. To test both hypotheses in consideration of Assumption 1, we have chosen to adapt, apply, and compare the following discrete-time approaches to customer decision support in cloud spot markets:

1. The binomial tree approach of Cox et al. (1979)
2. The binomial tree approach of Tian (1993)
3. Expectation optimization

Cox et al. (1979) were the first authors to develop a discrete-time version of the famous option pricing model by Black and Scholes (1973). They modeled the stochastic movements of an underlying and a matching option as a binomial tree. They prove that this model converges toward the Black-Scholes formula for decreasing-length time increments. Tian (1993) modified Cox et al.'s (1979) binomial tree formulae by matching the discrete-time process's skewness with the continuous-time process. Via numerical simulations on stock prices, Tian demonstrates that this model improves the accuracy of the convergence toward the Black-Scholes model. Although there are other derivatives of Cox et al.'s option pricing model (e.g., Amin 1991; Jarrow and Rudd 1983; Leisen and Reimer 1996), our approaches already provide valuable insights into discrete-time ROA's potential as a tool for decision support in cloud spot markets. Whereas Cox et al. (1979) and Tian (1993) do not model the time-of-day-specific patterns of their underlying, we apply both approaches in their native form and with this model extension (to test Hypothesis 1).

II.2.4.2 Binomial Tree Approaches without Time-of-Day Specific Patterns

In the following, we present Cox et al.'s (1979) and Tian's (1993) traditional approaches without consideration of the time-of-day-specific spot price patterns, which we introduce afterward.

Assumption 2: Cloud spot prices are log-normally distributed, while the returns of cloud spot prices are normally distributed.

Following Mazzucco and Dumas (2011), we assume that the returns of cloud spot prices are normally distributed (and that cloud spot prices are therefore log-normally distributed). In respect of EC2 spot prices, this assumption is "adequate but not perfect, as the distribution of the spot prices is more heavily-tailed" (Mazzucco and Dumas 2011, p. 297).

Assumption 3: Cloud customers are risk-neutral in their decisions.

Since both Cox et al. (1979) and Tian (1993) develop their approaches by assuming normally distributed returns and risk-neutral decision makers, we also require these rather technical assumptions. For the sake of our model's simplicity and in the light of our valid results, we consider these limitations adequate.

Cox et al. (1979) and Tian (1993) apply a binomial tree to model their underlying's stochastic process. The tree starts at the current point in time ($\mathrm{t} = \mathrm{t}_0 = 0$) before forking in discrete time increments into future nodes (i.e., future price levels) up to the option's expiration (denoted $\mathrm{t} = \mathrm{T}$). Consequently, at each node, with the exception of end nodes, the underlying is expected to move either in an upward or a downward direction. Cox et al. (1979) and Tian (1993) describe the binomial tree by means of the following parameters: $\mathrm{u} \leq 1$ and $\mathrm{d} \leq 1$ are constant factors for the (expected) extent of the underlying's upward and downward movements within one time increment. Both approaches depend on the historical return volatility $\hat{\sigma}$ and the risk-free interest rate $\mathrm{r_f}$ (which are both constant in these traditional models). A condition is that $\mathrm{u} * \mathrm{d} = 1$ and $\mathrm{u} > 1 + \mathrm{r_f} > d$. Moreover, $\mathrm{p} \leq 1$ is the constant probability of the underlying moving in an upward direction. Conversely, $1 - \mathrm{p}$ is the constant probability of a downward movement. The approaches by Cox et al. (1979) and Tian (1993) suggest the following formulae to derive the expected price development in an arbitrary time increment t to $t+1$:

$$S(t+1)_u = S(t) * u \tag{5}$$

$$S(t+1)_d = S(t) * d \tag{6}$$

In Figure II.2-2, we illustrate an exemplary binomial tree for our underlying (cloud spot prices).

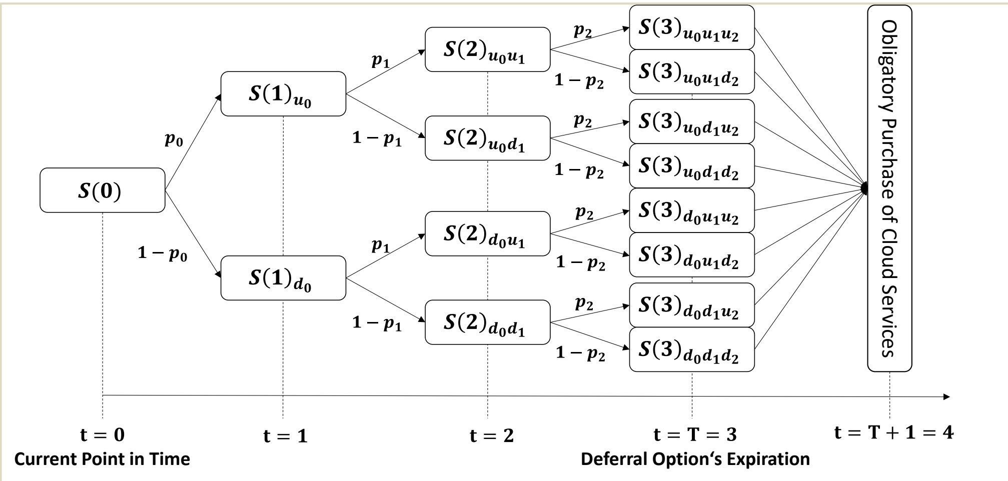


Figure II.2-2: Exemplary Binomial Tree for a Deferral Option with Three Remaining Time Increments

Under consideration of Assumptions 2 and 3, we can apply Cox et al.'s (1979) formulae:

$$u = e^{\hat{\sigma} * \sqrt{\Delta t}} \tag{7}$$

$$d = e^{-\hat{\sigma} * \sqrt{\Delta t}} \tag{8}$$

$$p = \frac{e^{r_f * \Delta t} - d}{u - d} \tag{9}$$

The parameter Δt quantifies the time increments between the decision nodes in the binomial tree, which is $\Delta t = 1$ in our case. Similarly, we can apply Tian's (1993) formulae, which (only) differ in terms of the u and d:

$$u = \frac{V}{2} * e^{r_f * \Delta t} * \left(V + 1 + \sqrt{V^2 + 2V - 3}\right) \quad \text{with } V = e^{\hat{\sigma}^2 * \Delta t} \tag{10}$$

$$d = \frac{V}{2} * e^{r_f * \Delta t} * \left(V + 1 - \sqrt{V^2 + 2V - 3}\right) \quad \text{with } V = e^{\hat{\sigma}^2 * \Delta t} \tag{11}$$

In both approaches, modeling the underlying's binomial tree is the prerequisite for option pricing. In each of the tree's nodes, a cloud customer must decide on whether to exercise the deferral option (i.e., to purchase cloud services) or not (i.e., to wait for another time increment). After exercising the deferral option, the optimization terminates. If the customer does not exercise the deferral option at time $t = T$ at the latest, he/she reaches the individual deadline in the next discrete time step ($t = T + 1$) and must purchase cloud services then. Technically speaking, modeling a deadline is already an extension of Cox et al.'s (1979) and Tian's (1993) traditional models, which Fridgen et al. (2016) introduced for the former approach. Both approaches start option pricing by analyzing the possible exercise values in the binomial tree's end nodes:

$$C(T) = \max\{X - S(T); 0\} \tag{12}$$

$S(T)$ is the expected cloud spot price at a specific end node in the binomial tree at time T. X is the exercise or strike price of the deferral option, which we explain later. If X is greater than $S(T)$, exercising the option in T is preferable, leaving the deferral option with a value greater than zero; however, if it is not, the customer should wait for one time increment and purchase cloud services at the individual deadline.

For every decision node that is $n \in \{1, \dots, T\}$ periods before T, the customer can compute the deferral option's value by applying the following formula by Cox et al. (1979):

$$C(T - n) = \max\left\{\begin{matrix} X - S(T - n); \\ p * C(T - n + 1) + (1 - p) * C(T - n + 1) \end{matrix}\right\} \tag{13}$$

Except for the end nodes in T, each decision node receives two values: that of the immediate cloud service purchase (i.e., the deferral option's exertion at that time) and that of deferring the purchasing decision for (at least) one time increment (i.e., the "time value" of exercising it later). The latter requires an algorithm for a probability-weighted valuation, since, from a single decision node's perspective, the tree forks into an upward and downward direction. The maximum of both values constitutes the deferral option's value at the relevant decision node. Note that since both approaches conduct the option pricing from the end nodes in T to root t_0, computing the time values of every decision node for $t = T - n$ can draw on already computed option values in $t = T - n + 1$. The algorithm terminates as soon as it obtains the deferral option's value in t_0 (i.e., the current point in time). Cloud customers can now compare the value of "exercising immediately" and "exercising later," deciding accordingly. If customers decide to wait for the next time increment, they need to update the observable price information and repeat the binomial tree construction and the option evaluation. Note that if customers can only purchase cloud services at certain times (i.e., at certain decision nodes), the deferral option complies with a Bermudan call option (or even with a European call option if they can only decide in $t = T$). Modeling a Bermudan (or European) call option only means modifying Equation 13 for non-decision nodes by removing the right and value of the immediate exertion.

II.2.4.3 Modeling Time-of-Day-Specific Patterns

We follow Fridgen et al. (2016) as follows to model the time-of-day-specific spot price patterns in order to test Hypothesis 1:

- Since we evaluate the monetary value of temporal flexibility in the short term (i.e., a maximum of several hours), the risk-free interest rate is insignificantly low, and we can set $r_f = 0$.
- We consider the time-of-day-specific spot price patterns by assuming *mean reversion*, i.e., for each discrete time step, the spot price is expected to move ("revert") to either the mean price level or according to the mean return, historically observed at the respective time of day. The same applies to volatilities.
- In keeping with both the traditional models created to evaluate options in capital markets, we treat these mean-reverting movements like discrete dividend payments.
- We model binomial parameters time-dependently, i.e., u(t), d(t), and p(t), because of the time-of-day-specific volatility patterns $\hat{\sigma}(t)$.

While Fridgen et al. (2016) extend the approach by Cox et al. (1979) with mean reversion to the time-of-day-specific mean price and volatility patterns, we also apply Tian's (1993) model and mean reversion to the time-of-day-specific mean return patterns. Financial asset pricing usually exhibits stationary mean returns, but non-stationary mean prices (Rossi and Spazzini 2014), which makes the former preferable for deriving predictions in these markets. Stationarity makes historical data a more appropriate estimator of future movements. As we could not find any related work concerned with stationarity analysis in cloud spot markets, we apply both approaches to model time-of-day-specific patterns and compare them.

In the following, we present relevant extensions of Equations 5 and 6 given the time-of-day-specific mean prices and returns.

Equations 5 and 6 with time-of-day-specific **mean prices** (Fridgen et al. 2016):

$$S(t+1)_{u_t} = S(t) * u(t) + \theta * (\hat{S}(t+1) - S(t)) \tag{14}$$

$$S(t+1)_{d_t} = S(t) * d(t) + \theta * (\hat{S}(t+1) - S(t)) \tag{15}$$

Equations 5 and 6 with time-of-day-specific **mean returns**:

$$S(t+1)_{u_t} = S(t) * u(t) + S(t) * \theta * \hat{R}(t) \tag{16}$$

$$S(t+1)_{d_t} = S(t) * d(t) + S(t) * \theta * \hat{R}(t) \tag{17}$$

Parameter $\theta \in [0,1]$ expresses the mean-reversion speed, controlling the speed with which the process reverts to the time-of-day-specific mean price or return patterns. A mean-reversion speed of $\theta = 1$ implies complete mean reversion during one time increment. In contrast, $\theta = 0$ implies no mean reversion.

Additionally, we model the strike price $X(t)$ as the (time-dependent) opportunity costs of exercising the option during the flexibility window before the deadline. Hence, $X(t)$ depicts the expected cloud spot price if the customer were to wait until the obligatory purchase in $T + 1$, i.e., $X(t) = S(T+1)$. The deferral option can therefore be interpreted as an option to buy before the individual deadline at relevant opportunity costs $X(t)$. At every decision node in the tree, we compute $X(t)$ as follows (for, respectively, the mean prices and the returns):

$$X(t) = S(t) + \theta * \left(\hat{S}(t+1) - S(t)\right) + \cdots + \theta * \left(\hat{S}(T+1) - S(T)\right) \tag{18}$$

$$X(t) = S(t) + \theta * S(t) * \hat{R}(t) + \cdots + \theta * S(T) * \hat{R}(T) \tag{19}$$

Technically, common option pricing approaches assume a constant strike price and ROA literature has been criticized for violating this assumption (Ullrich 2013). Fridgen et al. (2016) therefore keep the strike price constant; however, they sacrifice savings by not allowing an update of the strike price when receiving new market information. If the strike price can develop stochastically, an option pricing approach must explicitly take the relevant process for deriving the option's value correctly into account. The following reasoning allows us to apply a valid stochastic process for the strike price: As the strike price only depends on one stochastic factor $S(t)$, we obtain exactly one value for $X(t)$ at each decision node in $S(t)$'s binomial tree. Note that our definition of opportunity costs $X(t)$ does not comprise a further inconvenience regarding the customer's willingness to defer the purchase of cloud services, but only takes cost differences into account due to the volatile spot prices and the individual flexibility window.

Table II.2-1 summarizes all the real options approaches that we adapt, apply, and compare.

	Traditional (without time-of-day-specific patterns)	**With time-of-day-specific price patterns**	**With time-of-day-specific return patterns**
Cox et al. (1979)	✓	✓ **(Fridgen et al. 2016)**	✓
Tian (1993)	✓	✓	✓

Table II.2-1: Real options approaches applied to schedule flexible demand in cloud spot markets

When one applies Cox et al.'s (1979) and Tian 's (1993) traditional approaches, determining the optimal point in time to purchase cloud services is trivial. Following established option pricing theory, by early exercising American call options on underlying assets that pay no dividends (in our case, that do not consider the time-of-day-specific patterns) cannot be optimal (Hull 2014; van Hulle 1988). The same would apply to continuous-time models, such as those of Black and Scholes (1973). Both approaches would therefore not early exercise the option, but instead wait until $t = T$ to decide to either purchase at that time (at a price $S(T)$) or to wait for the deadline at $t = T + 1$ to purchase at a price $S(T + 1)$.

In addition to our real options approaches, we apply naive expectation optimization to test Hypothesis 2. In t_0, naive expectation optimization compares the currently observable price information with the expected prices in each upcoming time step in the flexibility window. The expected prices equal the historically recorded mean prices at the relevant time of day. Expectation optimization suggests that in order to purchase cloud services, customers should choose the time with the lowest expected spot price. Compared to our real options approaches, this naive approach does not consider return volatilities.

II.2.5 Evaluation and Sensitivity Analysis

Simulations are a rigorous evaluation technique (Gregor and Hevner 2013). We therefore conducted historical simulations on our EC2 dataset (Section II.2.3) to evaluate our approaches regarding their suitability to quantify and exploit the monetary value of short-term temporal flexibility in cloud computing demand. We implemented our approaches by means of Microsoft Excel with Visual Basic for Application macros and performed statistical tests in R. In randomly assembled scenarios that could have occurred in the past, we analyzed how well our approaches would have realized spot price savings. Our macros followed the following steps in each simulation run:

1. Select an approach (cf. Table II.2-1 or naive expectation optimization).
2. Select a random date and time of day from the historical time series as the starting point (between January 1, 2015 and December 30, 2016).
3. Select a random temporal flexibility window $\mathrm{TFW} \in \{1,2,\dots,12\}$ [increments]. Initially, the increment length IL (i.e., the time between two decision nodes) was constant at $\mathrm{IL} = 60$ [min].
4. For real options approaches with the time-of-day-specific patterns: Select a random mean-reversion speed $\theta \in \{0, 0.25, 0.5, 0.75, 1\}$ and a reference timespan $\mathrm{RTS} \in \{7, 30, 60, 90\}$ [days]. From the chosen starting point in time (2.), look back RTS days in the past to build expectations of the time-of-day-specific price (or return) and the volatility patterns.
5. Run the specific approach's algorithm.
6. After termination (i.e., after the purchase of cloud services), compare the purchase price to the spot price S_0 that was viable at the beginning of the TFW, and which a purchase without temporal flexibility would have realized. Compute the realized absolute and relative savings. With this information, divide the realized absolute savings by the maximum possible absolute savings within the TFW (which the algorithm would have obtained if perfect information were available), in order to compute the exploitation of the existing savings potential.

We distinguish two types of parameters: exogenous (scenario) and endogenous (model) parameters. IL, TFW, and starting time are exogenous parameters drawn to construct a simulation scenario. In contrast, approach selection, RTS, and θ are endogenous parameters. Both parameter types differ in the cloud customers' possibility to freely select endogenous parameters, although they might not be able to influence the exogenous parameters. Hence, in order to maximize their savings, cloud customers try to select endogenous parameters optimally. We conduct and analyze the results of six million simulation scenarios, one million for each approach, which approximates the maximum number of rows in our Microsoft Excel worksheets. Since Cox et al.'s (1979) and Tian's (1993) traditional approaches optimize identically (cf. Section II.2.4.3), we summarize both models in one approach. Table II.2-2 depicts our results.

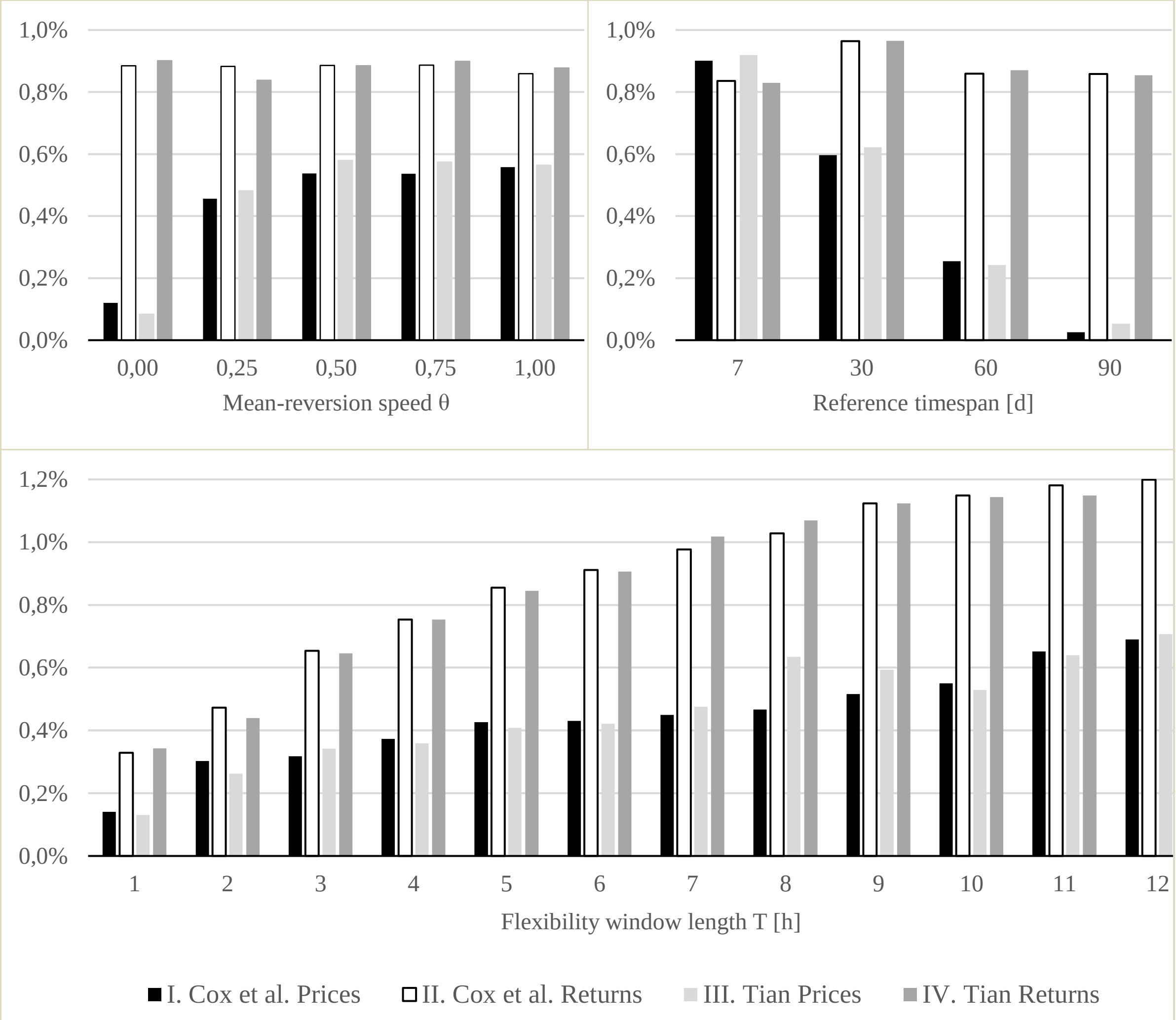
<table>
<tr><th rowspan="2"></th><th colspan="3">Savings with random parameters</th><th colspan="3">Savings after configuration with optimal θ and RTS</th></tr>
<tr><th>Averaged absolute savings to S_0 [¢]</th><th>Averaged relative savings to S_0 [%]</th><th>Exploitation of savings potential [%]</th><th>Averaged absolute savings to S_0 [¢]</th><th>Averaged relative savings to S_0 [%]</th><th>Exploitation of savings potential [%]</th></tr>
<tr><td rowspan="2">I. Cox et al. (1979) with price patterns</td><td rowspan="2">0.03649</td><td rowspan="2">0.80813</td><td rowspan="2">21.76075</td><td colspan="3">$\theta = 1$, $RTS = 7d$</td></tr>
<tr><td>0.06857</td><td>1.51294</td><td>40.45341</td></tr>
<tr><td rowspan="2">II. Cox et al. (1979) with return patterns</td><td rowspan="2">0.05682</td><td rowspan="2">1.25749</td><td rowspan="2">33.65950</td><td colspan="3">$\theta = 0.25$, $RTS = 30d$</td></tr>
<tr><td>0.06474</td><td>1.43051</td><td>37.49308</td></tr>
<tr><td rowspan="2">III. Tian (1993) with price patterns</td><td rowspan="2">0.03761</td><td rowspan="2">0.83261</td><td rowspan="2">22.26482</td><td colspan="3">$\theta = 1$, $RTS = 7d$</td></tr>
<tr><td>0.07337</td><td>1.61352</td><td>40.91032</td></tr>
<tr><td rowspan="2">IV. Tian (1993) with return patterns</td><td rowspan="2">0.05707</td><td rowspan="2">1.26403</td><td rowspan="2">33.93849</td><td colspan="3">$\theta = 0$, $RTS = 30d$</td></tr>
<tr><td>0.06763</td><td>1.49416</td><td>38.53289</td></tr>
<tr><td>V. Traditional Cox et al. (1979) and Tian (1993)</td><td>0.00929</td><td>0.20560</td><td>5.51305</td><td colspan="3">Not available</td></tr>
<tr><td>VI. Expectation Optimization</td><td>0.05572</td><td>1.23367</td><td>33.08806</td><td colspan="3">Not available</td></tr>
<tr><td colspan="7">Two-sample t-test: Reject H_0 hypothesis that the mean savings of V ≥ the mean savings of I–IV with optimal θ and RTS → approaches I–IV preferable***
Two-sample t-test: Reject H_0 hypothesis that the mean savings of VI ≥ the mean savings of I–IV with optimal θ and RTS → approaches I–IV preferable***
*** represents a significance level of 0.1%, ** a significance level of 1%, and * a significance level of 5%</td></tr>
</table>

Table II.2-2: Evaluation Results of Applied Approaches before and after Configuration of Endogenous Model Parameters

Overall, the results favor Hypotheses 1 and 2. More precisely, statistical two-sample t-tests indicate maintaining the null hypothesis that, after configuration, approaches I–IV yield superior averaged relative savings and exploit more savings potentials than the traditional approaches (V) and the expectation optimization (VI). In contrast to approaches I–IV, V does not model mean reversion, approach VI does not model volatility, and approaches V and VI are impossible to configure without parameters θ and RTS.

In respect of arbitrary random parameters, Table II.2-2 illustrates that approaches II and IV yield superior averaged savings compared to approaches I and III. However, as this relationship reverses when configuring all four approaches with optimal θ and RTS, the performances of approaches I and III are comparatively more dependent on their parameters. In Figure II.2-3, we show how the averaged relative savings reacted to altering parameters (*univariate sensitivity*).

Figure II.2-3 indicates that the performance of approaches I and III depends significantly on the selection of θ and RTS. More precisely, the performance depends strongly on recent historical price information (shorter RTS), which indicates fast changing price levels in our EC2 dataset. Moreover, since a higher θ improves the results significantly, historical price information seems to be a valuable predictor. The performance of approaches II and IV also depends significantly on the RTS selection. As a longer RTS is optimal in this case, our dataset shows slower changing return levels than price levels. The insignificance of θ indicates that relative savings depend less on the approaches' capability to predict the time-of-day-specific return levels. A longer TFW increases the option values by increasing the action flexibility (Hull 2014), which is in line with common option pricing theory. Figure II.2-4 uses histograms to illustrate these four approaches (after configuration with optimal parameters).



Two-sample t-test: Reject H_0 hypothesis regarding I*** & III*** that the mean savings of $(\theta < 0.5) \geq$ the mean savings of $(\theta \geq 0.5)$ → higher θ preferable

Two-sample t-test: Cannot reject H_0 hypothesis regarding II & IV that the mean savings of $(\theta < 0.5) \geq$ the mean savings of $(\theta \geq 0.5)$ (no significance)

Two-sample t-test: Reject H_0 hypothesis regarding I*** & III*** that the mean savings of $(RTS > 7) \geq$ the mean savings of $(RTS = 7)$ → shorter RTS preferable

Two-sample t-test: Cannot reject H_0 hypothesis regarding I & III that the mean savings of $(RTS \neq 30) \geq$ the mean savings of $(RTS = 30)$ (no significance)

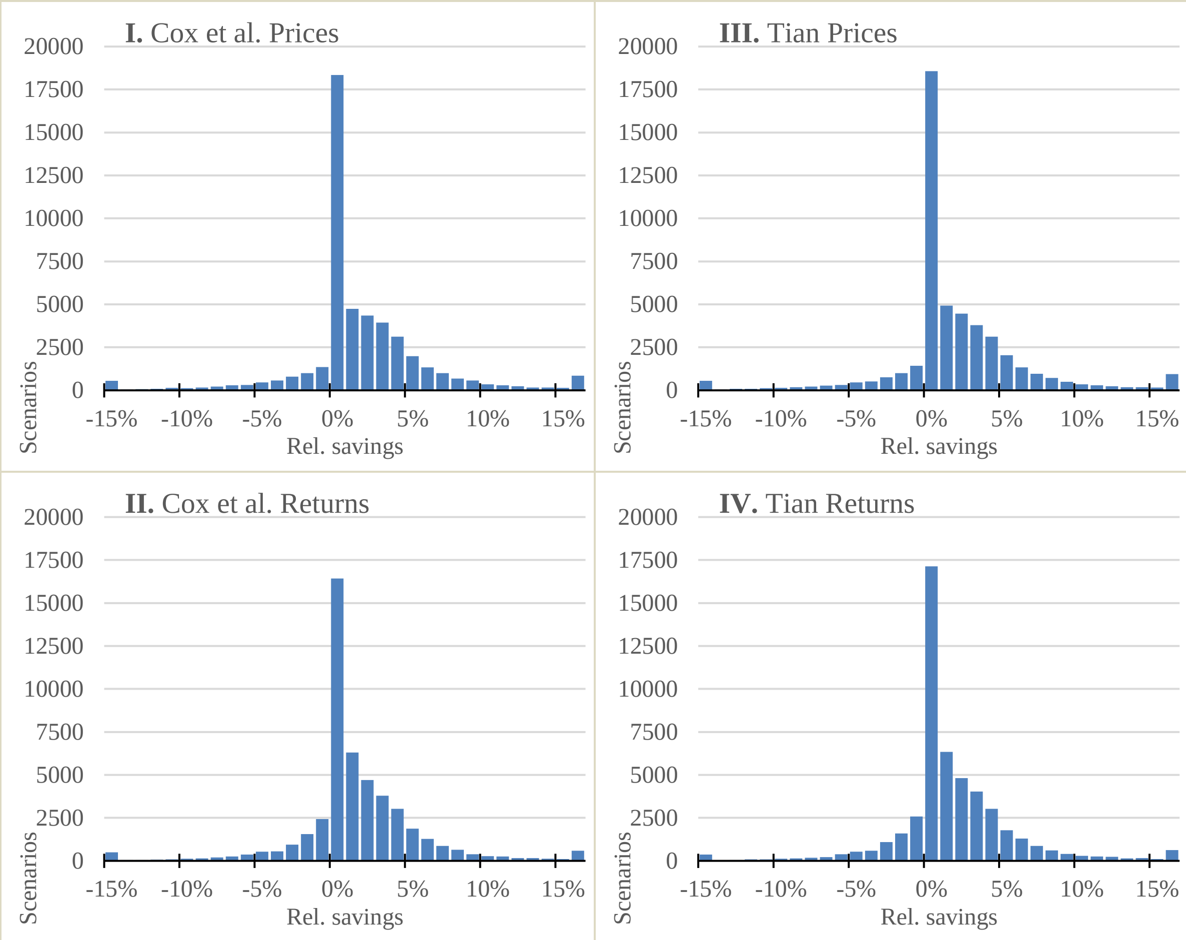
Two-sample t-test: Cannot reject H_0 hypothesis regarding II & IV that the mean savings of $(RTS > 7) \geq$ the mean savings of $(RTS = 7)$ (no significance)

Two-sample t-test: Reject H_0 hypothesis regarding II*** & IV*** that the mean savings of $(RTS \neq 30) \geq$ the mean savings of $(RTS = 30)$ → $RTS = 30$ preferable

Two-sample t-test: Reject H_0 hypothesis regarding I–IV*** that the mean savings of $(TFW \leq 6) \geq$ the mean savings of $(TFW > 6)$ → longer TFW preferable

*** represents a significance level of 0.1%, ** a significance level of 1%, and * a significance level of 5%

Figure II.2-3: Univariate Parameter Sensitivity of Averaged Relative Savings for Approaches I–IV

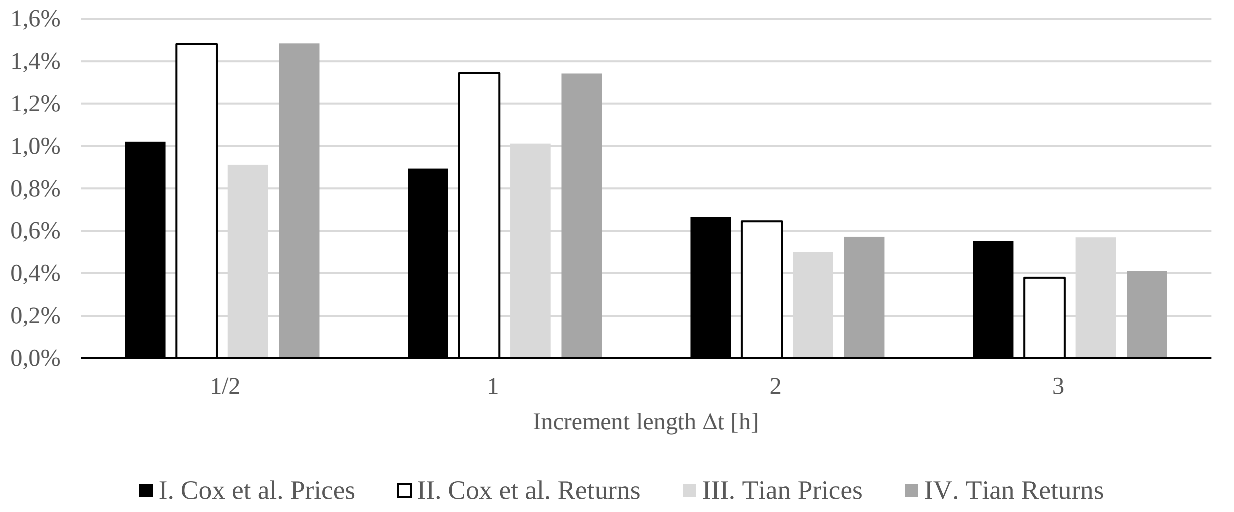


Two-sample t-test: Cannot reject H_0 hypothesis that the mean savings of Cox models ≥ the mean savings of Tian models (no significance)
Two-sample t-test: Reject H_0 hypothesis that the mean savings of return models ≥ the mean savings of price models → price models preferable***
*** represents a significance level of 0.1%, ** a significance level of 1%, and * a significance level of 5%

Figure II.2-4: Histograms of Relative Savings for Approaches I–IV with Optimal θ and RTS

Figure II.2-4 indicates that modeling time-of-day-specific price patterns instead of returns patterns is preferable (but only when configuring these models). According to Table II.2-2, applying approaches following Tian (1993) instead of those following Cox et al. (1979) is preferable, although not statistically significantly. The Tian (1993) approaches may be slightly better performing due to the increasing accuracy of their convergence toward the Black-Scholes model (cf. Section II.2.4.1). The better performance of modeling time-of-day-specific price patterns indicates that historical price information is a better estimator of spot price development over a few hours than return information. However, as approaches I and III's performances decline strongly with longer RTSs, this relation might reverse with longer TFWs (e.g., several weeks). Future research could analyze this hypothesis.

Finally, we run another one million simulated scenarios to test approaches I–IV's sensitivity to IL. We therefore randomize $\text{IL} \in \{30, 60, 120, 180\}$ [min], while we keep $\text{TFW} = 6\text{h}$ (a multiple of all IL) and the unconfigured parameters. Figure II.2-5 shows that longer ILs tend to yield lower averaged relative savings. This observation is plausible, as a longer IL within a constant TFW reduces the number of decision nodes in the binomial tree and, therefore, the action flexibility to react to short-term spot price development.



Two-sample t-test: Reject H_0 hypothesis regarding I–IV that the mean savings of $(\text{IL} \leq 1) \geq$ the mean savings of $(\text{IL} > 1)$ → shorter IL preferable***

Figure II.2-5: Univariate Sensitivity of Averaged Relative Savings to Interval Length for Approaches I–IV

II.2.6 Discussion

Our evaluation results could lead to the assumption that an extension of the Tian (1993) model with a mean reversion to time-of-day-specific price patterns is preferable. Such a generalized assumption is not, however, valid, because our results are strongly dependent on our dataset of a single Amazon EC2 spot instance in a specific location, and on our chosen simulation parameters. We actually evaluated representative scenarios and parameter sets to demonstrate that ROA can be a suitable decision support method when customers, given their temporal flexibility and the uncertain spot price development, wish to purchase cloud services at minimal costs.

As a measure of uncertainty, volatility increases a real option's value (Hull 2014). Lower volatility decreases temporal flexibility's value, because it lets one expect fewer savings from spot price movement. When applying ROA to our EC2 dataset, we observed that its return volatilities yielded rather low savings. More precisely, our configured approaches I–IV's relative savings averaged about 1.5 percent. However, this is already equal to exploiting about 40 percent of the existing savings potential (on average, cf. Table II.2-2).

Nonetheless, our results are especially relevant for the following three reasons: First, cloud services are becoming cost-intensive for many companies. For example, if Snap Inc., which recently announced that it would spend $2 billion on Google cloud services over a five-year period (US SEC 2017), achieved realizable savings of 1.5 percent, this would amount to an absolute amount of $6 million per year. Second, other cloud spot instances exhibit higher return volatilities (Ekwe-Ekwe and Barker 2018) and, therefore, higher savings potentials than the one referred to in our dataset. Future research should therefore analyze and compare different cloud spot instances to identify promising application scenarios for our ROA. Third, we expect the return volatilities in multiple cloud spot markets to increase in the future, because the rapid standardization of cloud services should liberalize the market structures further. More cloud providers offering spot prices should also increase the competition and liquidity on the supply side. On the demand side, recent trends like *cloud bursting*, which prevents peak load in companies' data centers by adding external cloud resources (Lilienthal 2013), will increase demand for cloud services. The latter will lead to trading volumes growing, which will, in turn, increase the return volatility (Wang and Yau 2000).

If cloud customers intend to apply our ROA algorithms within, for instance, their batch job schedulers, they need to identify suitable computation jobs for deferral (e.g., training machine learning models). Moreover, job schedulers must integrate the relevant cloud service provider's API (e.g., Query API for Amazon EC2, or the AWS SDKs) to automatically compare spot prices and the job backlog. This approach takes the boundary conditions of cloud service providers' customers, such as the service level agreements with their own customers, into consideration, which allows them to optimally decide which jobs to outsource to their provider and at what time.

Furthermore, beside to AWS, our ROA is transferable to emerging cloud spot markets: Recently, the Deutsche Börse Cloud Exchange, the Cloud Commodities Exchange Group, and the Massachusetts Open Cloud Exchange have initiated market places that provide spot prices. One could also apply our ROA to other domains, such as electricity and surge pricing, as long as some time-of-day-specific spot price patterns reoccur: Since we build on Fridgen et al.'s

2016 approach, electricity market researchers could inversely utilize our approaches. Surge pricing has also seen the first research on price forecasting (e.g., Laptev et al. 2017).

Cloud providers too can benefit from customers applying our approaches. They could, for instance, categorize spot instance bidders into more and less flexible customers. Flexible customers contribute to an improved server utilization (i.e., less idle resources), as they can "smooth out some of the computation requests with monetary incentives and lead to a more efficient use of Cloud infrastructure" (Li et al. 2016b, p. 7). According to Zhang et al. (2014), this more efficient resource allocation leads to higher provider revenue than fixed-price cloud services, which might be a competitive advantage in the market. To stimulate this benefit, providers could develop business models and provide cloud customers with dedicated decision support tools. However, flexible customers are more likely to avoid providers' price peaks, which may lead to a slight decline in the provider revenue, but could result in higher earnings due to the lower overall costs. Subsequent research could analyze these incentives for cloud providers to support or impede flexible cloud customers.

II.2.7 Conclusion, Limitations and Future Research

The rapid standardization and specialization of cloud computing services have led to the development of cloud spot markets on which cloud service providers and customers can trade in near real-time. The frequent changes in demand and supply give rise to spot prices that vary considerably throughout the day. Depending on the category of a service request, cloud customers often have temporal flexibility to execute their jobs. We apply ROA to the domain of cloud computing spot prices to quantify and exploit the monetary value of short-term temporal flexibility in cloud computing. We adapt different ROA approaches that, at consecutive points in time, decide whether to purchase cloud services immediately or to defer purchase. In our analysis of real-world data from an Amazon EC2 spot instance, we identify time-of-day-specific price patterns. Adapting existing ROA approaches to these patterns, we demonstrate the benefits of such approaches for cloud customers.

Our modeling approaches have technical limitations that subsequent research could address. First, we assume a normal distribution of returns, which does not necessarily hold true for cloud spot prices. Second, anomalies such as technical issues at the cloud provider might cause immediate and unpredictable price movements (*spikes*) that our stochastic process cannot predict. Third, for reasons of complexity, we limit our research to discrete-time models, although analytical approximations of or numerical solutions for continuous-time models and decision making would offer more action flexibility. Fourth, we limit our discrete-time models to extensions of Cox et al.'s (1979) and Tian's (1993) approaches.

Besides temporal flexibility, cloud customers could also exploit their spatial flexibility, as cloud spot prices still lack liquidity and are not necessarily arbitrage-free given the different providers and locations (Cheng et al. 2016; Fridgen et al. 2017). Further influencing factors, such as the home bias, amplify arbitrage opportunities, which cloud customers could seize by buying and selling cloud capacity. Future research could therefore integrate the optimization of temporal and spatial flexibility.

Cloud customers, service providers, and scholars may embed the proposed ROA in their decision support systems to optimize the execution of variable-time requests in cloud spot markets. This novelty has the potential to not only generate monetary benefits, but to also increase cloud spot markets' adoption.

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II.3 Research Paper 3: "Toward Strategic Decision Support Systems for Systemic Risk Management"

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Abstract:

The globalization and digitalization of production and businesses increases interdependencies and complexity of (digitized) value networks. Companies increasingly face lack of transparency issues and are therefore not able to consider their environmental and technological embedment for important management decisions. This development makes companies more and more vulnerable to systemic risks, i.e., risks that usually occur at local parts in (digitized) value networks but threaten to spread to (distant) companies' related business operations. The management of systemic risks is a complex task for companies and requires the assistance of IS technology. We believe that new decision support systems (DSS) will provide a significant tool to assist in the management of these complexities and opacities, endemic to systemic risk management by gathering, processing, and interpreting manifold information originating from internal and external sources of a focal company. In this paper, we conduct research to address the issue described above by developing a generic architecture of a strategic DSS designed specifically to manage systemic risk, and by discussing major challenges for which solutions are required in order to implement such a DSS. We pave the way for important future research by defining selected research questions and conclude that the realization of a strategic DSS to support systemic risk management requires joint efforts of interdisciplinary researchers, as well as practitioners.

II.3.1 Introduction

Over the past decades, the increasing globalization of production and businesses has enabled companies to open new customer markets and reduce costs by exploiting new possibilities such as offshoring, outsourcing, international joint ventures, and acquisitions. These developments have resulted in the emergence of increasingly fragmented and distant value networks in which specialized companies cooperate on a global scale. The resulting interconnections of business partners are growing due to just-in-time inventory levels, as well as just-in-sequence production, and the manifold dependencies on inter-organizational information systems (IS) and IS service providers (Basole & Rouse, 2008). Hence, as lack of global transparency of value networks increases, single companies are now encountering difficulties with the complexity of their business operations related to important management decisions. This development results in a situation such that the business is increasingly vulnerable to risks from correlated defaults, which stem from a focal company's value network. We refer to those risks that originate at a small number of nodes and move to the entire value network as "*systemic risks*." Systemic risks are located within the structural composition of a value network as well as the inherent interdependencies (Neitzke, 2007), and "are mostly based on cascade spreading effects in networks" (Helbing, 2012, p. 276). Such risks may occur at any node on the value network and affect other business partners due to interdependencies in flows of goods, financial flows and flows of information. The term "*systemic risk*" is closely related to "*supply chain risk,"* commonly used within the supply chain (risk) management literature. Supply chain risks comprise "any risks for the information, material, and product flows from the original supplier to the delivery of the final product to the end user" (Jüttner, Peck, & Christopher, 2003, p. 203). In contrast to systemic risks, which are (to date) especially researched in the context of interbank markets (Bartle & Laperrouza, 2009) and supposed to impose large-scale economic impacts (Roengpitya & Rungcharoenkitkul, 2011), supply chain risks may also be limited to operational risks with (usually) less economic impact (Tang, 2006). Yet, our focus in this paper is on strategic levels of networked (non-financial) companies, i.e., we focus on risks that may jeopardize the existence of a focal company due to major dependencies and interconnections within a dynamic value network. In addition, although existing definitions of supply chain risks are widely used, we regard this term as neither intuitive nor suitable to describe risks beyond immediate value creation and supply chain management. In particular, certain risks such as dependencies of focal companies on their (IT) service providers or on financial institutions are usually not included within the context of supply chain risks. For this reason, we continue to use the broader terms "*value networks*" and *"systemic risks*" instead of "*supply chains*" and "*supply chain risks*."

There are already some examples of systemic risks in value networks, which have resulted in large economic damages. In October 2011, a flood in Thailand caused production outages in the local hard disk industry that produced 70% of all hard disk motors (a central hard disk component) worldwide. Consequently, hard disk producers such as Seagate and Western Digital halted production for weeks and thus, these manufacturers were not able to meet their customer demand of computer manufacturers like Dell or Lenovo, or online sellers such as Newegg. As a result, market prices for hard disks rose threefold and, a year later, prices were still up 60% to 90% relative to prices prior to the flood (Randewich, 2011). Another example is the recall of 7.8 million vehicles in the US in 2014 due to defective driver-side airbags manufactured by the Japanese component supplier, Takata that affected at least the following ten automobile manufacturers: Toyota, Honda, Mazda, BMW, Nissan, Mitsubishi, Subaru, Chrysler, Ford, and General Motors. The defective airbags exploded when an automobile was involved in an accident, dispersing metal shards. The linkage of the defective air bags to at least five customer deaths and several serious customer injuries resulted in the filing of Class-action lawsuits naming several automobile manufacturers (besides Takata) as defendants. This litigation cost the defendants substantial financial penalties; in addition, the defendant manufacturers incurred costs to replace the defective airbags and they suffered from damage to their quality brand images (Bennett, Rogers, & Kubota, 2014). According to a study of Hendricks and Singhal (2005) of 885 disruptions of value networks, the occurrence of (systemic) risks negatively affected the operating performance (mostly sales) as well as the return of the stock price of the affected companies that continued for a period of up to two years. Accordingly, the management of systemic risks in complex and interconnected value networks is of great strategic importance. More recently, emerging trends in technology such as digitalization, the internet-of-things, and cyber-physical (production) systems have accelerated the intensity of these vulnerabilities. There is an increase in integration of value networks within information and communication technology that connects physical production systems, products, services, business partners, and customers across business (local and global) borders. Despite the numerous benefits of digitized value networks such as the flexible production of custom products at costs comparable to those for mass production ("lot size one"), this development leads to even more value network interconnections, complexity, and therefore vulnerability of single companies. Moreover, new kinds of security risks emerge, since IS are increasingly opened and integrated across company-borders to enable collaboration and thus, allow for peripheral activities with criminal intentions on a high degree of anonymity. This threat was exemplified by a cyber-attack on a steel plant in 2014 reported by the German Federal Office for Information Security (BSI, 2014). After they intruded the office network of the plant, the hackers manipulated critical control components, which allowed them to access the separated production network. In the course of the attack, the state of the blast furnace was undefined and it was not possible to shut it down in a controlled manner. The situation resulted in severe damage to the blast furnace and other machinery of the plant (BSI, 2014). This example describes a conventional, low-digitized production facility. The threat potential significantly increases in businesses that are dependent on just in time and just-in-sequence production, and participate in highly interconnected, digitized value networks.

Traditionally, a corporate risk management comprises different steps of a risk management process, such as risk identification, evaluation, control, and monitoring. Though spreadsheet calculations created by applications such as Microsoft Excel provide custom solutions for specific risk management purposes (Jüttner & Ziegenbein, 2009, p. 209; Power & Sharda, 2007, p. 1051), the resulting diverse and silo structured application landscapes are often inconsistent, do not share an integrated database, and thus, possess functional limitations so they cannot support comprehensive risk management activities. In particular, such IT applications are not capable of handling the increasing complexities and opacities caused by the dynamics of digitized value networks. This is also concluded in the "*governance, risk, and compliance report*" (GRC) by SAP (2015) which interviewed 1,010 executives with responsibilities for GRC in their organizations. The survey states that the increasingly complex business and risk environment is severely challenging companies and that only one in ten organizations are fully satisfied with their current GRC tools, technologies, and processes. A helpful first step for many focal companies would be the integration of different risk management processes as well as corresponding application systems in order to optimize collaboration between risk managers relative to sharing of important (systemic) risk relevant information. Such an integration enables the design, development and implementation of decision support systems (DSSs), i.e., an IS that supports complex decision making by providing solutions to semi-structured or unstructured problems through accessible user interfaces (Huang, Sun, Nie, Qin, & Zhang, 2010; Shim et al., 2002). In particular, a custom DSS is required to manage complexities and opacities of systemic risk management by gathering, processing and interpreting manifold information from inside and outside a focal company. A customized DSS has the potential to improve decision quality, reduce response times, lower risk management costs, and establish new forms of collaboration within company borders as well as with external business partners. The creation of such a DSS, however, creates several challenges and open-end questions, which have to be approached by both researchers as well as practitioners. In this paper, we address these challenges and open-end questions by developing a generic architecture for a strategic DSS designed specifically to support systemic risk management, a prerequisite effort to the creation of such a DSS:

RQ: What is an appropriate generic architecture for a DSS that is capable of identifying systemic risks, analyzing those risks, and providing strategic decision support in digitized value networks?

Following Broniatowski (2015), we define a generic architecture as “generalized structure that may be applied to a technical system […] in order to indicate how information flows between system components” (p.1547). Therefore, our generic architecture is a template for a future DSS that abstractly relates necessary technological components of a risk management IS, based on (systemic) risk relevant information flows. It is the first step within a larger project that requires joint efforts from both (interdisciplinary) researchers as well as practitioners in order to enable companies whose business operations are dependent on digitized value networks to deal with systemic risks. The organization of the remainder of our paper is as follows. Section II.3.2 provides an overview of the various directions of existing research on the topic. In Section II.3.3, we derive the generic DSS architecture based on an appropriate functional design. In Section II.3.4, we discuss challenges and selected research questions regarding the future realization of a strategic DSS for systemic risk management. Finally, Section II.3.5 presents the conclusion, identifies limitations, and provides an outlook for future research.

II.3.2 Related Work

Shang et al. (2008) define DSS as "a class of information systems intended to assist managers in decision-making" (p. 2). Traditionally, a DSS provides "more comprehensive support for human control systems [...] while maintaining and strengthening human qualities" (Strohmaier & Rollett, p. 4). Since the concept of a DSS emerged in the 1970s, supporting human qualities to control decisions has been more important in this field of research than replacing the humans with computers (Arnott & Pervan, 2008). DSS is a fast growing field of IS research (Suduc, Bizoi, Cioca, & Filip, 2010) and we continue to analyze DSS literature within the special application field of corporate and public risk management in order to locate our research subset. Second, we present literature on supply chain risk management, which investigates topics closely related to our objective, and further elaborate why this discipline, however, is insufficient to develop measures against systemic risks. Moreover, this part illustrates the importance of IS research and our approach in particular. Third, we extend previous arguments by identifying additional challenges in the emerging field of digitized value networks.

II.3.2.1 Decision Support Systems in Risk Management and Methodology

In general, literature that researches DSS within the application field of risk management addresses different areas of application. On an operational level of business-management, Fang and Marle (2012) built a simulation-based DSS approach for project risk management, which integrates risk identification, risk evaluation, risk control, and risk monitoring. Similar, Dey (2001) develops a DSS for project planning by using "*analytical hierarchy process*" as a structured technique to analyze project risks as well as decision trees for deriving appropriate risk responses. Mahdi and Alreshaid (2005) use analytical hierarchy process to build a DSS for the proper selection of project delivery methods that integrates risk and performance measures. To prevent production system failures, Puente et al. (2002) developed a DSS based on the qualitative failure mode and effect analysis. Their method is built on structured expert knowledge and establishes risk priority categories. Li and Liao (2007) proposed a decision support framework for operations in dynamic alliances, which combines core competences of different companies. Their approach is capable of identifying and evaluating various types of risk factors in multi-attribute decision-making.

On a tactical level of business-management, Hong and Lee (2013) proposed a DSS for procurement risk management. By considering correlated demand, yield, and price uncertainties, their approach includes the design of a robust purchasing plan for supplier selection and order allocation. Converging toward our objectives, Güller et al. (2015) proposed a decision support model of supply chain risk management. Their framework integrates an agent-based simulation model, real-time databases as well as risk management processes and is suited to manage disruption risks proactively before they occur. However, we want to go beyond those authors' application area, which is restricted to directly observable flows of goods and business collaborations (i.e., operational and tactical levels of business-management). Our objective is to set a direction for a strategic DSS that is capable of capturing systemic risks that arise from widely ramified as well as complex network structures and (informational) interdependencies. In particular, we want to contribute to this area of literature by developing a generic DSS architecture that defines the foundation for an intelligent IS, which is capable of supporting risk managers by deriving risk information for strategic corporate decisions.

Literature on strategic DSS, as applied to risk management, is limited to critical infrastructure and large-scale public construction projects, i.e., applications to public authorities which are usually in possession of (or are able to obtain) crucial information about important (spatial) properties, involved parties, and interdependencies. To prioritize renewal of water pipeline projects, Moglia et al. (2006) built a DSS that contains a risk management approach to predict cost as well as pipeline failures. Snediker et al. (2008) developed a spatial DSS to mitigate disruption risks in (critical) network infrastructures, identified from several sources such as natural disasters, terrorism, human errors, etc. Their approach facilitates the examination of "*what-if*" planning scenarios in public disaster management by examining geographic and topologic implications. Levy (2005) discussed advances in multiple criteria decision making and respective implementations of DSS for flood risk management. He presents a DSS architecture that he applies to the flood planning and management of the Yangtze River, China. Horita et al. (2015) developed another spatial DSS for flood risk management. Their approach combines data sources from wireless sensor networks with geographic information volunteered from ordinary citizens in high-risk areas. Kumar and Viswanadham (2007) focus on risk management in major construction supply chains and suggest a DSS framework by applying a case-based reasoning approach. This IT-enabled solution is useful in preventive and reactive risk management.

Although these are just examples that illustrate the scope of existing research on DSS in risk management, we were, despite intensive efforts, not able to identify literature on any strategic DSS applied to systemic risk management. In our opinion, this situation is not surprising, primarily because of the fact that external information, i.e., information from outside of the company that is necessary to monitor and analyze (inter-) dependencies of business operations and associated systemic risks, is usually incomplete or unavailable. We want to contribute to this research gap by proposing a generic architecture for a strategic DSS in systemic risk management and by conducting a subsequent discussion on necessary future research with particular emphasis on the gathering and processing of unstructured (external) input information. We chose to conduct a comprehensive interdisciplinary approach, although this has not allowed our research to study fine-grained details of every related research discipline. In particular, we did not conduct a structured state-of-the-art approach, since this would not have enhanced the explanation of our artifact. An interdisciplinary approach is reasonable, considering that no research discipline (e.g., finance, supply chain management, and operations research) can solely manage the many challenges of systemic risk management. IS and especially DSS research, however, have the ability to merge interdisciplinary knowledge as we particularly demonstrate in Section II.3.4.

II.3.2.2 Supply Chain Risk Management

In order to enable corporate risk management to include risks beyond company boundaries, a new line of research was already established called “*Supply Chain Risk Management*” (SCRM). Literature on this topic has increased significantly since the beginning of the 21th century (Ceryno, Scavarda, Klingebiel, & Yüzgülec, 2013; Colicchia & Strozzi, 2012; Sodhi, Son, & Tang, 2012; Tang & Nurmaya Musa, 2011). This may be due to catastrophes related to supply chains such as the 9/11 attacks (USA, 2001), hurricane Katrina (USA, 2005) and the big earthquake as well as tsunami (Indian Ocean, 2004) (Qazi, Quigley, & Dickson, 2015; Thun & Hoenig, 2011), and from current developments in globalized, interconnected and dependent industries as stated in our introduction. Ho et al. (2015) define SCRM as “an inter-organisational collaborative endeavour utilising quantitative and qualitative risk management methodologies to identify, evaluate, mitigate and monitor unexpected macro and micro level events or conditions, which might adversely impact any part of a supply chain” (p. 5036). The essence of this definition emphasizes the need to extend traditional risk management processes through more intensive inter-organizational collaboration in order to include adverse effects that may be due to organizational or environmental parameters that are external to a focal company ("*externalities*"). SCRM literature has already developed several approaches to account for such risk management extensions (e.g. Giunipero & Aly Eltantawy, 2004; Manuj, Esper, & Stank, 2014; Manuj & Mentzer, 2008b; Nishat Faisal, Banwet, & Shankar, 2006; Norrman & Jansson, 2004; Nyoman Pujawan & Geraldin, 2009; Peck, 2006; Ritchie & Brindley, 2007).

There are three important research gaps that systematically appear throughout this line of research. First, Qazi et al. (2015) conducted a comprehensive and systematic review of SCRM literature for the years 2000 to 2014 and concluded that existing SCRM approaches predominantly use qualitative methodologies rather than quantitative techniques. A review of SCRM literature between the years 2000 to 2010 (Ghadge, Dani, & Kalawsky, 2012) identified this result. The researchers state, "the preferred methodology has been qualitative" (p. 324). To illustrate this first research gap from a practitioner's perspective, Blackhurst et al. (2005) conducted a multi-industry empirical study in which all interviewed supply chain managers emphasized the need for quantitative assessment of critical nodes in the supply chain. Second, the few existing quantitative models for risk assessment usually do not include dependencies between several supply chain risk factors (Badurdeen et al.; Qazi et al., 2015). However, a literature review of Colicchia and Strozzi (2012) for the years 1994 to 2010 revealed that the consideration of dynamic interactions among risk sources and supply chain partners is a "*key challenge*" for effective supply chain risk identification and assessment. Third, most quantitative models are inappropriate for strategic decisions. Tang (2006) reviewed various quantitative models of mitigating supply chain risks. He states that most existing approaches focus exclusively on the management of operational rather than strategic supply chain risks (such as customer demand and supply risks, or price risks) and are therefore not capable of capturing the complexity of an entire supply-chain. However, this is a necessary precondition in order to be able to manage systemic risks such as threats of major disruptions. We conclude that there is a lack of appropriate quantitative risk management approaches for strategic decision support.

An explanation of this lack is because circumstances necessary to create quantitative models for risk management usually require (historical) information for appropriate calculations. Though information gathering is already challenging within company boundaries, creating quantitative models of a supply chain level is an even more difficult task. The SCRM literature actually emphasizes the importance of (external) information management and, in particular, information sharing between supply-chain partners, which is a shift toward inter-organizational learning (Manuj & Mentzer, 2008a). Peck (2006) states that "few would dispute the almost universally held belief […] that […] information sharing […], is a route to more effective supply chain risk management" (p. 134). Yet, Christopher and Peck (2004) state that "there has not been a history of sharing information either with suppliers or customers" (p. 17). Manuj et al. (2014) conducted a survey of supply chain managers in which many interviewees express the desire to evaluate SCRM strategies, external information gathering; however, remains an open challenge. Blackhurst et al. (2005) observe supply chain managers' need for "relevant, timely and credible information" (p. 4075), since supply chain visibility "is the new battleground" (Blackhurst et al., 2005, p. 4073) in competitive environments and "core element of supply chain risk mitigation" (Blackhurst et al., 2005, p. 4073). Besides mitigating risks, supply chain managers must implement information sharing in order to develop competitive advantages (Giunipero & Aly Eltantawy, 2004), especially when the technology or market environment change rapidly (Fynes, B'Urca, & Voss, 2005). In particular, researchers found either theoretically (Cachon & Fisher, 2000; Christopher & Lee, 2004; Ha & Tong, 2008; Lee, So, & Tang, 2000; Li, Sikora, Shaw, & Woo Tan, 2006; Lin, Huang, & Lin, 2002) or empirically (Rai, Patnayakuni, & Seth, 2006; Wong, Lai, Cheng, & Lun, 2015; Zhou & Benton jr., 2007) that information sharing can be very beneficial in contractual and operational terms which do not directly affect risk management.

In summary, literature on SCRM emphasizes the importance and benefits of (external) information management and, in particular, information sharing, but usually lacks solutions to the corresponding difficulties that, to date, "do not feature within the core" of SCRM research (Ghadge et al., 2012, p. 328). Hence, although SCRM is already an interdisciplinary field of research (Manuj & Mentzer, 2008b; Peck, 2006), there remains the need for further integration of interdisciplinary knowledge (Tang & Nurmaya Musa, 2011). The use of IS could improve information sharing and therefore risk management across the supply chain (Gupta & Nandan, 2014). In particular, the research field of IS enables the creation of a strategic DSS in systemic risk management and is therefore essential for our objective. Such a DSS must possess the capability to quantify systemic risks as well as interdependencies between risk factors; this represents a "*grand challenge*" of IS research (Mertens & Barbian, 2015) and a major research requirement in SCRM.

II.3.2.3 Digitalized Value Networks

The concurrent digitalization of value networks, which comprises technological trends such as the Internet-of-Things or cyber-physical (production) systems, promises business potential but also imposes significant challenges for corporate risk management (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014). For instance, the increasing organizational and technological interconnectivity between companies leads to ever-complex business dependency structures as well as information-based dependencies, which decrease transparency of business operations and hence, complicate risk management efforts. Further, the real-time constraint of highly optimized, flexible and automated production infrastructures increases the importance of accurate information flows for proper operation of production processes (Hessmann, 2013; Schuh, Potente, Varandani, Hausberg, & Fränken, 2014; Yoon, Shin, & Suh, 2012) and digitized value networks become increasingly vulnerable to information-based risks such as unavailability, inaccessibility, inaccuracy and unaccountability of information (systems) (Smith, Watson, Baker, & Pokorski II, 2007; Yoon et al., 2012). Information-based risks can spread through the entire digitized value network due to informational dependency structures that are independent of the physical connections. Hence, information-based risks can take the property of systemic risks by possessing high damaging potential and must be included in operative and strategic risk management approaches in order to derive (preventive) risk mitigation measures. Further, in the course of digitalization, the importance of (digital) service providers increases significantly, as digital services enable key functionalities for digitized value networks such as real-time information sharing, communication, data storage, and processing. However, digital service providers, not directly involved in the value creation of a company, are inadequate included in existing SCRM approaches.

Literature on systemic risks, so far, is focusing on interbank markets in response to the financial crisis of 2007 (e.g. Acharya, Pederseen, Philippon, & Richardson, 2010; Adrian & Brunnermeier, 2009; Bartram, Brown, & Hund, 2007; ECB - European Central Bank, 2010; Huang, Zhou, & Zhu, 2009; Lehar, 2005). The transfer of developed concepts and the adaption to the application field of digitized value networks is still missing. There are first publications that already deal, at least to some extent, with digitalization and the effects on risk management. For example, Keller and König (2014) develop a reference model for service oriented value networks based on actors, risks, and dependency structures of digital cloud networks. Hertel (2015) presents a framework for structuring threat scenarios and risk sources in digitized production infrastructures, i.e., so-called smart factories. Becker et al. (2013) developed a conceptual modeling language to specify interaction routines in service networks and a modeling method based on social construction of networks. Further, taking advantage of the tremendous amounts of data becoming increasingly available, Caron et al. (2013) exploit the potential of data measures and process mining in the field of risk management. Pika et al. (2016) use event logs of information systems that record execution of business processes to evaluate the overall process risk and to predict process outcomes. However, similar to most SCRM literature, those authors apply qualitative approaches for structuring risks. Quantitative methods of risk identification, evaluation and mitigation as well as economic risk measures are still not developed, and therefore, are subject to future research. Digitalization requires the consideration of the many dimensions of both corresponding potentials and threatening risks.

II.3.3 Generic RMSS Architecture

The previous section provides a sufficient indication that in order to be capable of counteracting systemic risks, researchers, and practitioners must think beyond the capabilities of existing risk management approaches. Inter-organizational information sharing is already used to facilitate procurement as well as delivery processes, reduce storage costs, and to enable outsourcing as well as customer-specific products. However, besides objectives of cost reduction and business development, information sharing and gathering can generate benefits in terms of corporate risk management. The objective of this paper is to derive a generic architecture toward a strategic DSS in systemic risk management. In the following, we refer to such a system as “*Risk Management Support System*” (RMSS) and we begin by presenting an appropriate functional design (Figure II.3-1) that integrates a technological interface for external information sharing and gathering. Then we use this perspective to motivate the components of our generic DSS architecture.

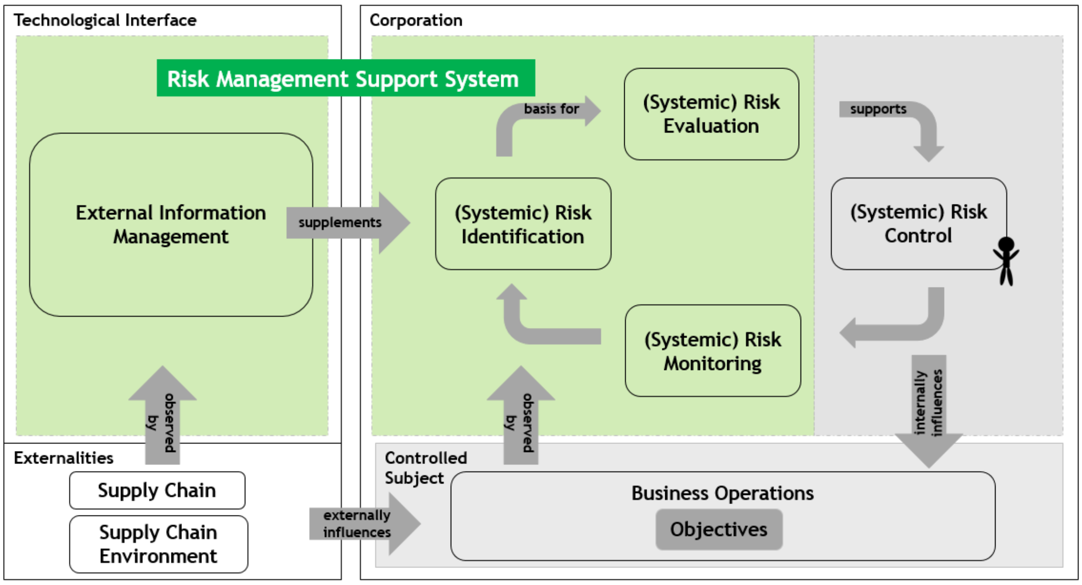

Figure II.3-1: RMSS functional design

A RMSS is the vision of a comprehensive IT-based DSS for systemic risk management, which emphasizes the need for human-driven risk control and decision-making. DSS assist the (human) risk controller to "discover what would happen if a series of decisions are taken" (Arán Carrión et al., 2008, p. 2360). Therefore, a RMSS must provide the risk controller with an opportunity to select specific "*what if*"-scenarios. For example, if the focal company intends to award new delivery contracts to suppliers, the risk manager should be able to request risk estimates of different sourcing strategies by using an appropriate user interface. While risk control is a function executed solely by humans, conduction of other actions of the RMSS occurs autonomously, following human frame conditions. Human experiences and estimations, however, can be provided as additional input to enrich the data set (e.g., expert knowledge for closing data gaps). We build the RMSS functional design exemplar using a common 4-step risk management process for the observation and control of business operations. Thereby, business operations "comprise the dealings of an organization with its stakeholders including customers, suppliers, and employees with regards to everyday activities" (Okoe, Amartey, & Arkorful, 2015, p. 345). In addition, we propose a new step in the risk management process, called "*External Information Management*" (EIM). The objective of EIM is to share and gather information with and about supply chain participants, and (digital) service providers as well as their surrounding environment. The technological components of EIM can be located inside as well as outside a focal company, integrated as a monitoring component of the RMSS, with the function to enable an automated information input stream. Therefore, EIM supplements the RMSS with additional input information processed to identify, evaluate, and monitor (systemic) risks. Provision is made for the human risk controller to provide information about externalities and their (potential) influence on business operations. Based on this new process step, (in particular) strategic decisions such as choices about new business partners, product diversification and international site selection, can be supported in terms of integrated risk and return management. To summarize, the RMSS has to be an extensively networked online system, which is able to execute queries, analyze new as well as previously stored information, and conduct computations in real-time.

To converge to a definition of RMSS, we classify and design a generic RMSS architecture, a template for a future DSS and therefore a fundamental requirement for the development of applicable IS to support systemic risk management. The objective of the generic RMSS architecture is to create abstract relationships among the necessary technological components based on (systemic) risk relevant information flows. In order to appropriately classify and design a generic RMSS architecture, we follow the "*Expanded DSS Framework*" of Power (2002) and Power (2008), who distinguish five categories of DSS technologies depending on their main purposes:

- **Communications-driven DSS:** "use network and communications technologies to facilitate decision-relevant collaboration and communication" (Power, 2008, p. 129).
- **Data-driven DSS**: "provide tools for access and manipulation of large databases or data warehouses storing large amounts of data" (Hassan, Eldin, & El-Ghazali, 2015, p. 26). Input data is already structured (Power & Sharda, 2007).
- **Document-driven DSS:** use "computer storage and processing technologies to provide document retrieval and analysis" (Power, 2008, p. 130). Input data is still unstructured (Power, 2008).
- **Knowledge-driven DSS:** "suggest or recommend actions based upon knowledge that has been stored using Artificial Intelligence or statistical tools" (Power & Sharda, 2007, p. 1045). They approach problems "which are normally resolved by a human expert" (Hassan et al., 2015, p. 26).
- **Model-driven DSS:** provide decision support with "algebraic, decision analytic, financial, simulation, and optimization models" (Power & Sharda, 2007, p. 1044). They "use limited data and parameters provided by decision makers to aid decision makers in analyzing a situation, but in general large databases are not needed for model-driven DSSs" (Power, 2008, p. 126).

In accordance with Power and Sharda (2007) who stated that an IS may also include several of the above approaches, we conceive our RMSS to be an "*integrated system*." This is because none of the outlined categories is sufficiently comprehensive to grasp RMSS complexity, which is necessary to deal with systemic risks. The integrated system combines components from different DSS categories as illustrated in Figure II.3-2.

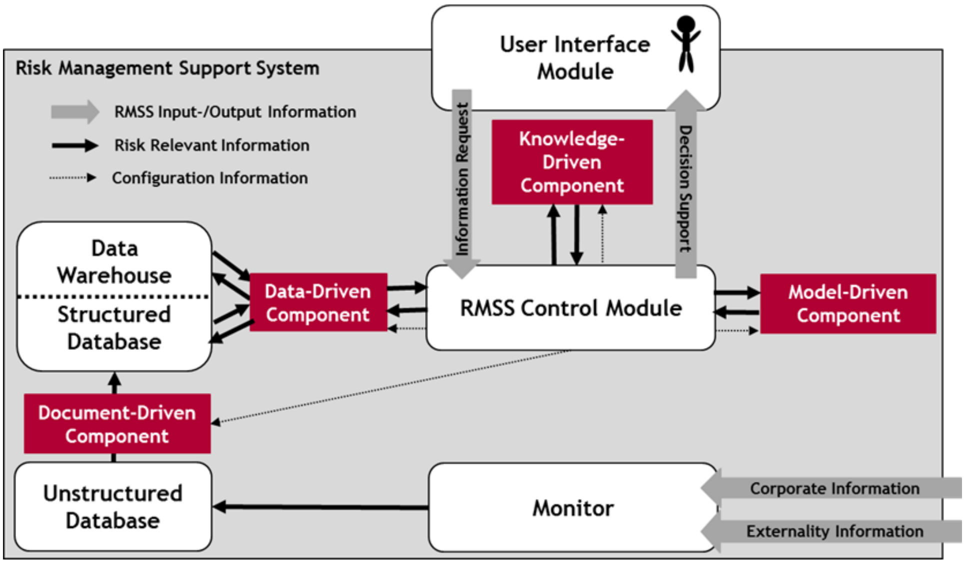

Figure II.3-2: RMSS generic architecture

The RMSS collects input from three sources: First, the objective of the "*Monitor*" is to observe internal influences on business operations, i.e., information within company boundaries. In an example of new procurement contracts, this could comprise order details (e.g., business volumes, time schedules, and requirements specification), corporate information (e.g., strategic goals, balance sheet numbers, and regulations), and existing supplier information (e.g., offering prices, delivery times, existing collaborations, and mutual trust). Second, the Monitor integrates (or is connected with) a technological interface that supports EIM in order to share and gather information from outside the focal company that might influence business operations. In the case of our example, the latter may consist of market information (e.g., supplier competition, product sourcing alternatives, and currency and commodity price fluctuations), supplier vulnerability and criticality information (e.g., natural hazard and country risk indices, credit ratings, supplier product diversification, and supplier dependencies including dependencies on (digital) service providers). Third, the human risk controller describes the decision problem to the system by specifying an information request within the "*User Interface Module*." Those three input sources initialize the system to create decision support, which is the output of the RMSS. Since the Monitor works independent of specific support requests, it must be preconfigured to support a broad range of search patterns, with access to a variety of data sources. Moreover, it may be necessary to create additional user interfaces to manually enter information. The Monitor passes input information to an "*Unstructured Database*," which gathers all delivered (meta) data. Such information can be manifold and provided in different data formats. Since database capacities are limited, there must be a first step of data processing, which filters, structures and stores required information for further usage. Performance of this task occurs via an intelligent component, which we refer to as the "*Document-driven Component*." Although this component is not a DSS in terms of the Expanded DSS Framework, we attribute special properties of a Document-driven DSS to it. The Document-driven Component extracts, categorizes and summarizes information qualitatively from the Unstructured Database (similar to a Document-driven DSS of Power (2002)), which can subsequently be used for special (e.g. numeric) purposes. The output of the Document-driven Component is structured information (managed by a Structured Database) that can be accessed on demand by a "*Data-driven Component*," which is the connecter to the central "*RMSS Control Module*." Following the concept of a Data-driven DSS, this intelligent component enables the RMSS to "analyze, display and manipulate large structured data sets" (Power, 2002, S. 124). In addition, the Data-driven Component can assess information from a Data Warehouse, which (in general) provides long-term storage of historical and consolidated data to improve decision support (Dewan, Aggarwal, & Tanwar, 2013). While an arbitrary number of Structured Databases can exist (e.g., for separately managing structured internal and external information), the Data Warehouse must be unique. Since the RMSS frequently receives new input information, detailed designs of Document-driven and Data-Driven Components have to build on Big Data and Semantic Web Research. The RMSS Control Module receives information requests from the User Interface Module and coordinates the creation of appropriate decision support. After receiving an information request, this intelligent component compares the inquiry to existing knowledge, which is stored within a "*Knowledge-driven Component*." Similar to a Knowledge-driven DSS, such a component provides basic expertise (e.g., rules or procedures) that is derived from historical data (i.e., from previous information requests) or manually implemented default knowledge. In addition, it is capable of conducting qualitative risk analysis by applying human expert knowledge and visualization measures (e.g., risk matrix, or risk maps). The Knowledge-driven Component informs the RMSS Control Module regarding required input information for qualitative (systemic) risk analysis. For modeling and quantifying (systemic) risks, however, the RMSS Control Module submits an inquiry to the "*Model-driven Component*," a derivative of a Model-driven DSS. Depending on the specific information request, this component chooses appropriate analytical or simulation models and requests required input information from the RMSS Control Module. The RMSS Control Module in turn passes input information requests of the Model-driven and Knowledge-driven Components to the Document-driven and Data-driven Components. These components apply their analytic algorithms to the (Un-) structured Database(s) and the Data Warehouse and respond. After receiving the required input information, the Model-driven Component executes the computations to generate the quantitative risk identification, evaluation, and monitoring while the Knowledge-driven Component performs the qualitative analysis defined by those three steps of the risk management process. The processing of input information requests, subsequent computation as well as analytic procedures iterate for each of the three risk management process steps and cannot be performed concurrently (risk evaluation, for example, postulates previous risk identification). If necessary, the RMSS Control Module configures other intelligent components in order to adapt them to the user's specific information request (e.g. adapting semantic search terms within the Document-Driven and the Data-driven Components). Finally, the RMSS Control Module aggregates and delivers decisions support to the User Interface Module, thereby completing the decision support request. The information request as well as the system's response, recorded within the Knowledge-driven Component, extends the systems knowledge base. The RMSS is now ready to process the next human request for decision support. It is reasonable to implement a feedback function in which the user can assess the relevance and completeness of the decision support response in order to improve the RMSS knowledge database. Note that we did not implement a "*Communications-driven Component*" in our generic RMSS architecture, as we do not focus on distributed decision support; however, respective extensions may be reasonable in future designs. We believe that the first applications of the RMSS will be limited to very specific purposes (e.g., the estimation of tier-one supplier risk exposure for different single- and dual-sourcing strategies of key components) but we expect that the RMSS will evolve to a more complex DSS in the future.

II.3.4 Challenges and selected Research Questions toward future detailed designs

To date, our generic RMSS architecture is a rough concept of a risk management IS that is becoming a necessary tool for many (global) companies. Since many challenges must be addressed, the full implementation of such an IS remains into the future. To address these challenges, it requires joint efforts of researchers, representing interdisciplinary knowledge from diverse research disciplines, and practitioners, to demonstrate practical feasibility. In the following, we provide our contributions to such joint efforts by discussing some major RMSS challenges and selected research questions, thereby providing an orientation for future (IS) research. We structure our discussion along the following dimensions of our RMSS architecture: (1) information sharing and gathering, (2) information analysis, (3) information processing, and (4) decision support.

II.3.4.1 Technological interfaces for external information sharing and gathering

The RMSS Monitor integrates (or is connected with) a technological interface for EIM, i.e., an interface to obtain information about externalities and their (possible) influence on a focal company. Such a technological interface may be a shared digital database such that each supply chain participant can share its data and obtain external information from other participants. However, even if companies in a digitized value network are willing to share their data (c.f. next research question), it will be necessary that a central unit of organization exists, which provides the necessary coordination and IT infrastructure. Hence, a major challenge emerges from the fact that some organization must invest resources and effort to create and manage the necessary databases. It would be necessary to either form a supply chain board for coordination, or possibly commission an independent service provider. Regardless of the method preferred, most digitized value networks are opaque, complex, interconnected with other digitized value networks and heavily exposed to dynamic changes in composition and boundaries. This fact complicates communication and increases the costs of coordinating such a project. Assuming digitized value networks with several participants, the outlined situation is a perfect example of a "*public good game*," because a single company would prefer others to bear the costs and organizational effort. To summarize, shared digital databases are hardly appropriate for EIM.

In order to communicate with direct business partners, companies have already implemented so-called "*Inter-Organizational Information Systems*" (IOIS). IOIS, which were first mentioned by Barrett and Konsynski (1982), serve as a technological interface between (two or more) business partners, and support sharing of risk-relevant information. Prominent examples of IOIS are systems for vendor-managed inventory as well as collaborative planning, forecasting, and replenishment systems. However, the nature of systemic risks particularly requires communication beyond direct business partners. Existing approaches to enable communication between distant supply chain participants are product centric technological interfaces such as the EPCglobal Network. “*Product centric*” means that information is embedded within each single product, and not shared through digital databases. Although there are different product centric approaches, “the EPCglobal Network stands out among the rest because in 2003 it was authorized as a Global Standards I (GS1)” (Muñoz-Gea, Malgosa-Sanahuja, Manzanares-Lopez, & Sanchez-Aarnoutse, 2010, p. 480). The EPCglobal Network uses RFID tags (with unique identifiers) and readers to read and write product codes affixed to (semi) finished products. For example, Bi and Lin (2009) develop a methodology to discover digitized value networks by using the EPCglobal Network. They analyze information within a four-dimensional matrix and support the capability to map the network structure, quantities of the flows of goods and the time that individual goods remain at and move between digitized value network participants. However, the information that is available from EPCglobal, is not sufficient to manage systemic risks, since a focal company reads only product codes and related information of incoming and outgoing commodities. In particular, information about the flow of goods that is non-physical (e.g. IT services) and/or not directly connected with the focal company (e.g. competitors, and suppliers’ customers in different industries) cannot be accessed. While product centric approaches focus on decentralized information of individual products, other technological interfaces can build on bilateral information sharing between distant supply chain participants. Yao (1986) and Goldreich et al. (1987) provide the foundation for the so-called “*Secure Multiparty Computation*” (SMC), a subfield of cryptography, which enables the creation of information exchange software using peer-to-peer networks. “SMC allows mutually distrustful parties to jointly compute a functionality while keeping their inputs private” (Dachman-Soled, Malkin, Raykova, & Yung, 2011, p. 130). This technology can enable simultaneous information sharing without leakage of critical information and therefore increase the willingness of companies to participate in information sharing. For example, Fridgen and Garizy (2015) provide a first approach to use SMC in a digitized value network to discover networking structures by simultaneously preserving individual privacy. However, there remains the problem that some organization must (initially) bear the costs and organizational effort to develop and distribute the corresponding software. To date, technological interfaces that support information sharing and gathering are rarely developed, applied as well as researched upon frame conditions and capabilities. We state the following research question:

Q1: To support EIM, what are the technological interfaces that must be designed to appropriately enable and coordinate the (remote) sharing and gathering of (systemic) risk relevant information?

II.3.4.2 Information sharing incentives

Besides enabling and coordinating EIM, appropriate technological interfaces must ensure information sharing incentives. Companies usually have concerns regarding security, privacy and intellectual property (Li et al., 2006). In particular, the concern that information sharing primarily benefits a counterparty is a major disincentive (Lee & Whang, 2000; Mishra, Raghunathan, & Yue, 2007). Moreover, information sharing may require “the release of confidential and closely guarded financial and strategic information to partners who might have been or may later be competitors” (Du, Lai, Cheung, & Cui, 2012, p. 91). Even if those partners were confidential, there is a threat of information leakage to third parties. Li (2006) refers to this problem as the “*leakage effect*” as competitors may discover confidential information based on the actions of the informed parties. In particular, customers or suppliers of a focal company can use leaked information within upcoming negotiations. For these reasons, companies are frequently reluctant to share information with their network partners.

Q2: How can technological interfaces that support EIM limit a focal company’s concerns regarding security, privacy, as well as intellectual property and incentivize information sharing?

II.3.4.3 RMSS Database Systems

One purpose of the monitoring component of our generic RMSS architecture is the intention to collect unstructured (meta) information regarding the company and external influences. Depending on this component’s configuration, this may result in huge amounts of push-based data within short time periods. On the one hand, continuous data input streams might lead to data overflow errors and therefore possible loss of critical input information if data storage capacities are not sufficiently large. On the other hand, traditional database management systems are static, which means that information has to be stored before that data can be processed. Therefore, information within the database might be outdated or inaccurate. To cope with these challenges, a detailed design of our Document-driven Component must integrate modern database systems. In the early years of this millennium, research on “*Data Stream Management Systems*” (DSMS) raised with the objective to create administration software for continuous queries on large data streams (Abadi et al., 2003; Babcock, Babu, Datar, Motwani, & Widom; Chen, DeWitt, Tian, & Wang, 2000). DSMS "allow user to analyze the data-in-motion" (Gupta, Gupta, & Mohania, 2012, p. 50) and, in particular, the continuous extraction of risk relevant information. For example, a DSMS in our Document-driven Component can query unstructured input information from the Monitor according to the RMSS control module's configuration input. By using a DSMS, unstructured (static) databases might be dispensable and extracted input information can be stored directly in a Structured Database component as well as the Data Warehouse for further use. Another promising technology, "*Real-Time Database Systems*" (RT-DBS), are "an amalgamation of a conventional database management system and a real-time system" (Bestavros, A., Lin, K. J., & Son, S. H., 2012, p. 1). A RT-DBS not only optimizes for logical correctness (i.e., querying the required information) but also for temporal correctness which means that information has to be processed at the correct time under special consideration of deadlines (Safaei, Haghjoo, & Abdi, 2011). Although both objectives are important, such a system usually favors timeliness, a property that can be especially valuable in situations such that a risk manager requires contemporary decision support (Diallo, Rodrigues, & Sene, 2012). In contrast to a DSMS, a RT-DBS is only approximately real-time, since queries are highly frequented but not continuous, and data must be stored in an (unstructured) database prior to processing. However, if data input streams from the Monitor are highly volatile, a DSMS may encounter damaging traffic congestion in times of high activity (Gürgen, Roncancio, Labbé, Bottaro, & Olive, 2008), which is less a problem for a RT-DBS. A third kind of modern database system is an "*In-Memory Database"* (IMDB) which stores information within main memory. This enables fast access to the large volumes of data (Buhl, Röglinger, Moser, & Heidemann, 2013). In particular, applications for data processing can access the in-memory data directly (without disk access) and therefore increase transaction performance significantly. Yet, limited capacity is still (likewise in our case) a big problem for IMDB (Nishida & Nishi, 2012). Modern relational and multidimensional database systems are indispensable for managing input information within the RMSS. However, more research is required in order to clarify which technology (or combination of technologies) is preferable in order to cope with volatile amounts of unstructured input information. We state the following research question:

Q3: What are the appropriate database architectures that can support specific RMSS purposes?

II.3.4.4 RMSS Data Processing

By executing queries submitted by the RMSS control module, both the Document-Driven Component and the Data-driven Component must process risk relevant information from data that is resident within the (Un-) structured Database(s) and the Data Warehouse. A detailed design of both Components can consist of two types of software: Online transaction processing (OLTP) and online analytical processing (OLAP). OLTP is suited for executing ordinary and highly repetitive queries on detailed and current information (Chaudhuri & Dayal, 1997; Park, Park, & Won, 2015). For example, information transactions submitted to the Data-driven Component, backed by the Structured Database(s), may focus on recent financial figures and key performance indicators of the focal company, or exchange rates with foreign currencies. OLAP, on the other hand, is suited for complex queries and analysis of data. For example, if the RMSS control module requires a time-series and comparison of several exchange rates, then the Data-driven Component can use the OLAP capability to query the Data Warehouse and its long-term historical data. However, since misinterpretation of (especially unstructured) information is frequent, depending on vocabulary choice, the context, and data quality, the benefit offered by decision support is dependent upon the analytic capabilities of both software types. Today, there is still a need for OLTP and OLAP to integrate more accurate semantic data analysis (Gulić, 2013) which is particularly important for the RMSS, since correct interpretation of input data is a key to strategic decision support. Semantic data analysis is also an important and fast growing IS research field with the objective to manage the challenges posed by Big Data (Englmeier, 2015; Patel & Madia, 2016). Standards such as Linked Data are delivered by a larger number of data providers; these data providers create the foundation for more successful semantic data analysis activities in the future (Bizer, Heath, & Berners-Lee, 2009). We emphasize the need to transfer research of semantic data analysis to the creation of Document-Driven and Data-driven Components.

Q4: What is the appropriate data processing software for RMSS to support a robust level of OLTP and OLAP in order to enable the system to conduct semantic data analysis on risk-relevant input information?

II.3.4.5 Risk modeling languages

We believe that a RMSS enables the user to obtain strategic decision support. Such decision support may be both qualitative and quantitative statements regarding risk exposure due to different options of action. The creation of quantitative statements requires the system to possess risk modeling and assessment techniques, which our RMSS utilizes within the Model-driven Component. The modeling of systemic risks is crucial for subsequent risk assessment, and influenced by the selection of appropriate modeling languages. In the case of RMSS, an appropriate modeling language must fulfill three basic requirements. First, it has to be "*complete*" in terms of representing all relevant components and their relationship in a comprehensive model of risk origination and propagation. Second, it has to be "*consistent*" which means that rules and procedures do not yield contradictory results. Two identical basic situations with identical parameter settings must result in two identical outcomes. Third, it has to be "*simplifying*" in terms of reducing real-world problems to manageable complexity. In particular, a simplifying modeling language should allow for abstraction, formalization and modularization (Fridgen, Stepanek, & Wolf, 2014). Modeling languages that support (inter-) organizational risk management purposes have already been used in conjunction with the related research field of SCRM. Neiger et al. (2009) develop a modeling methodology to identify supply chain risks, based on value-focused process engineering (VFPE), a modeling language that "creates links between business processes and business objectives at the operational and strategic levels" (Neiger et al., 2009, p. 155). Mahfouz and Arisha (2010) use integrated modeling approaches (IDEF0 & IDEF3) to assess and mitigate rush order risks at both macro and micro levels of a supply chain. Their simulation model provides numerical measures as well as insights into sensitivities of relevant parameters. Fridgen et al. (2014) extend an approach of Wu et al. (2007) to model disruptions and their propagation in supply chains based on modular Petri Nets. They conclude that IS should manage the increasing complexity of value network and information flow. Wagner and Neshat (2010) build an approach to quantify and mitigate supply chain vulnerability using graph theory. To address the modeling of network interdependencies, Buldyrev et al. (2010) apply Erdős–Rényi networks (i.e., random graphs) and use their specialized model to describe cascade failures during the 2003 electrical blackout in Italy. These are only some examples that illustrate the variety of modeling languages that were already used for (inter-) organizational risk management purposes outside interbank market research. To the best of our knowledge, literature that provides a comparative analysis of modeling languages, their development potential with respect to completeness, consistency, simplicity, and general applicability to modeling systemic risks in digitized value networks does not exist. Therefore, with regard to our purposes, we state the following research question:

Q5: What comprehensive, consistent, and simplifying modeling languages are most appropriate in the sense that they have the most development potential for modeling systemic risks?

II.3.4.6 Risk assessment measures

Another important objective of the Model-driven Component is risk assessment. The quantification of risks within the RMSS might be twofold: First, since digitized value networks abstractly consist of companies (nodes) and their connections and dependencies (edges), we must consider the network analytic metrics, generally referred to as "*centrality measures.*" These are metrics that evaluate "the level of importance or influence of a node in a graph" which reflects "certain topological characteristics" (Chen, Choudhury, & Hero, 2016, p. 2). In other words, topological characteristics of a digitized value network provide information regarding the critical and vulnerable nature of certain companies within the network. For example, "*degree centrality*" can quantify the critical attribute ("*out-degree*") and vulnerable attribute ("*in-degree*") of a company, while "*closeness centrality*" as well as "*betweenness centrality*" provide information regarding both properties. Second, the quantification of (systemic) risks can be computed by applying "*risk measures*," a "functional that assigns a numerical value to a random variable which is interpreted as a loss" (Rachev, Ortobelli, Stoyanov, Fabozzi, & Biglova, 2008, p. 4). A popular risk measure, because of its simplicity, is the "*value-at-risk*" (VaR) that quantifies a threshold loss value for a given confidence level and period of time. The VaR is the most widely applied risk measure in finance (Peterson & Boudt, 2008) and has already been transferred into the context of SCRM (Lodree Jr & Taskin, 2008; Sanders & Manfredo, 2002; Zhang, Goh, Terhorst, Lee, & Pham, 2013). However, VaR approaches have several disadvantages, which occur commonly for systemic risks. First, this risk measure does not account for the average extent of damage beyond the given confidence level. This is a serious problem, since it would not be possible to calculate worst-case impacts from systemic risks. Second, many VaR approaches assume normally distributed losses, whereas systemic risks (such as natural disasters) usually exhibit heavy-tailed distributions, i.e., the probability for worst-case scenarios is higher than is assumed by a normal distribution of losses (Kousky & Cooke, 2010). Third, VaR approaches require historical data to estimate parameter values and/or perform historical simulations. This data is often not available due to the rarity and manifold nature of systemic risks and/or the absence of external information access. Fourth, VaR measures are not necessarily sub-additive, which means that the VaR of an entire company might exceed the sum of VaR of all business units. However, there is no evidence that systemic risks exhibit negative diversification effects. Another financial risk measure, which quantifies "the expected loss given that the loss is greater than or equal to the VaR" (Rockafellar & Uryasev, 2002, p. 1445), is the "*conditional-value-at-risk*" (CVAR) or "*expected shortfall*." Therefore, in contrast to the VaR, the CVaR would be able to account for worst-case impacts of systemic risks. Moreover, this risk measure is sub-additive, therefore eliminating two of the mentioned VaR disadvantages. Similar to the VaR, researchers suggest the transfer of CVaR to the (non-financial) context of SCRM, especially to support procurement decisions (Chen, Shum, & Simchi-Levi, 2014; Sawik, 2013; Zhang et al., 2013). The remaining issues with normally distributed losses and little historical data may be addressed using "*extreme value theory*" (EVT), a research field that provides methods to quantify risks with heavy-tailed distributions based on VaR and CVaR (Allen, Singh, & Powell, 2013; Singh, Allen, & Robert, 2013). EVT has already been transferred to SCRM (Ravindran, Ufuk Bilsel, Wadhwa, & Yang, 2010) and may be well suited for rare events such as systemic risks (Zhang, Zhang, & Zhou, 2009), characterized by a small amount of available information. However, if no information is available or it is not possible to guarantee information validity, a common occurrence in risk management practice, none of the mentioned centrality metrics or risk measures is able to provide reliable results. We state the following research question:

Q6: What centrality metrics and risk measures are most appropriate or possess the most development potential to quantify (systemic) risks; how do these metrics address missing or inaccurate information?

II.3.4.7 RMSS Learning Capabilities

Finally, we introduce an important research challenge to the development of a Knowledge-driven Component. A detailed design of this intelligent component may include concepts from the IS research field of machine learning with the objective of allowing a system to generalize beyond existing knowledge (Domingos, 2012). Existing knowledge within the RMSS may originate from two sources. First, a training set can be used (offline) to initialize machine learning during the development or maintenance of the system. Second, decision support during RMSS operation may be assigned (ex-post) with fitness values, for example, by analyzing human feedback and/or backtesting functions, which enable the system to continuously improve the quality of decision support (online) for individual user requirements. Following Domingos (2012), machine learning consists of three components. First, “*Representation*,” which comprises the formal language for the hypothesis space (e.g. neural networks, support vector machines); second, “*Evaluation*,” to compute fitness values for different options for action; and third, “*Optimization*,” for actual action selection, i.e., decision support in our case. To date, many different approaches for machine learning exist, even for purposes of supply chain management (Carbonneau, Laframboise, & Vahidov, 2008). However, there is no evidence in the literature that documents the techniques that might be most suited for the purposes of systemic risk management. Hence, we state the research question:

Q7: What machine learning techniques are most appropriate or have the most development potential to allow the RMSS to enable continuous improvement in decision support?

II.3.5 Conclusions and Discussions

The globalization and digitalization of production and businesses continues to increase interdependencies and complexities within (digitized) value networks. Hence, focal companies’ exposure to their dynamic environment is increasing, also increasing systemic risks, which jeopardizes their business operations and therefore their very existence. Decision support systems (DSS) can assist managers to manage the complexities and opacities in systemic risk management by gathering, processing and interpreting manifold information from inside and outside a company. The creation of such a DSS, however, creates challenges and unanswered questions, which require resolution by researchers and practitioners, working together.

In this paper, we contribute to the development of a strategic DSS created to support systemic risk management by developing a generic architecture and by discussing open challenges as well as selected research questions. The generic architecture is a template for future IS and therefore, a fundamental requirement, which relates necessary technological components, based on systemic risk relevant information flows. Our discussion of open challenges and selected research questions provides an orientation for future research and is another contribution to this interdisciplinary endeavor.

One limitation of our approach is the gap between our generic architecture and future practical implementations, which are, to date, merely a vision. Currently, we have not conducted a detailed study of requirements and possible use cases with practitioners that will be necessary to develop a RMSS detailed design. Moreover, the quantification of systemic risks with missing, incomplete, or inaccurate information is a major research challenge that will determine the performance capability of any future RMSS. To date, we are only able to pose corresponding research questions. Therefore, we especially encourage researchers in quantitative risk management to join our efforts in order to develop appropriate risk measures. However, we regard this paper as an important first step to motivate interdisciplinary and, in particular, IS research in systemic risks as well as to identify an initial approach to resolution that can be further developed and serve as a foundation for future research.

A reasonable next step for our research is to introduce and discuss our generic RMSS architecture using risk managers from companies that have already established a risk management implementation of strategic decision support. The further development of such systems is inevitable in order to manage the increasing threat of systemic risks. This objective should empower companies to manage not only the opportunities but also the challenges of production and business globalization and digitalization.

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III Decision Support for Risk and Return Management in Energy Flexibility Management

Section III deals with investment risk and return management in energy flexibility management. As the transition to renewable energy sources makes energy costs increasingly volatile and an important competitive factor in manufacturing, companies could profit from investing in the utilization and extension of their temporal flexibility when externally sourcing energy. Therefore, like in the case of digitized value networks, decision makers should recourse to *decision support systems* (DSSs), whose business logic is based on principles of integrated risk and return management and that help to optimally invest in demand response approaches. In this context, *Research Papers* (RPs) 4-7 contribute to the development of such DSSs considering specific decision-making situations.

The first research paper (RP 4) *"Providing Utility to Utilities: The Value of Information Systems Enabled Flexibility in Electricity Consumption"* (Section III.1) helps companies to lower their electricity costs by presenting a real options approach for evaluating and exploiting temporal flexibility in externally sourcing electricity from real-time spot markets. Regarding investment risk and return management, RP 4 contributes to risk and return quantification and control.

The second research paper (RP 5) *"Decision Support in Building Automation - A Data-driven Demand Response Approach for Air Conditioning Systems"* (Section III.2) follows a similar objective by minimizing expected electricity costs for the special use case of building air conditioning systems. Therefore, RP 5 also contributes to risk and return quantification and control.

The third research paper (RP 6) *"Demand Side Management: Entscheidungs-unterstützungssysteme für die flexible Beschaffung von Energie unter integrierten Chancen- und Risikoaspekten"* (Section III.3) assists companies in improving their energy flexibility management by providing functional requirements and a generic system architecture for respective DSSs. Thereby, RP 6 contributes to all four steps of investment risk and return management in an overarching manner.

The fourth research paper (RP 7) *"The Regional and Social Impact of Energy Flexible Factories"* (Section III.4) helps companies to utilize their energy flexibility potential by introducing a transdisciplinary research approach that considers technological, ecological, and social restrictions of different stakeholders. As this enhances a purely economic analysis, RP 7 contributes to risk and return identification of related investments.

III.1 Research Paper 4: "Providing Utility to Utilities: The Value of Information Systems Enabled Flexibility in Electricity Consumption"

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Published in:	Journal of the Association for Information Systems, 17(8), 537-563 Please note that this is an editorially revised version of the published journal article.

Abstract:

As the transition to renewable energy sources progresses, the integration of such sources makes electricity production increasingly fluctuate. To contribute to power grid stability, electric utilities must balance volatile supply by shifting demand. This measure of demand response depends on flexibility, which arises as the integration of information systems in the power grid grows. The option to shift electric loads to times of lower demand or higher supply bears an economic value. Following a design science research approach, we illustrate how to quantify this value to support decisions on short-term consumer compensation. We adapt real options theory to the design - a strategy that IS researchers have used widely to determine value under uncertainty. As a prerequisite, we develop a stochastic process, which realistically replicates intraday electricity spot price development. With this process, we design an artifact suitable for valuation, which we illustrate in a plug-in electric vehicle scenario. Following the artifact's evaluation based on historical spot price data from the electricity exchange EPEX SPOT, we found that real options analysis works well for quantifying the value of information systems enabled flexibility in electricity consumption.

III.1.1 Introduction

Faced with growing environmental concerns and a dependence on exporters of fossil commodities, several countries have begun transitioning their power supply from fossil and nuclear sources to renewable resources, such as solar and wind. The shift toward these intermittent energy sources makes electricity production increasingly fluctuate (Ludig, Haller, Schmid, & Bauer, 2011). For example, non-forecasted wind prompts peaks in electricity supply, which can destabilize the power grid and require costly balancing efforts. By itself, adjusting the supply curve through electricity storage would not be sufficient to balance the highly volatile supply and demand nor to offset the strain on the power grid, which has prompted the idea of intervening on the side of consumption as well (Palensky & Dietrich, 2011).

Business research describes “demand-side management” (DSM) as activities that influence the timing and magnitude of consumer demand for electricity to accommodate fluctuations of electricity production. Researchers consider DSM as an umbrella term (Feuerriegel & Neumann, 2014) and another common term, “demand response” (DR), as a subclass of such activities. Through incentives or varied electricity prices, DR activities induce changes in electricity consumption (Albadi & El-Saadany, 2008). Such measures tend to span minutes or hours, and electricity consumers decide to participate in DR programs voluntarily (Palensky & Dietrich, 2011). For our approach, we use the term DR, which includes load control.

“Advanced metering infrastructure” (AMI)—systems for measuring, collecting, transmitting, and analyzing energy usage data—is the IT enabling DR. AMI combines smart meters, which measure electricity consumption in time intervals, load control switches, and bidirectional communication streams between electric utilities and consumers (Callaway & Hiskens, 2011; Li et al., 2013). As such, utilities can remotely control demand by, in particular, emitting control signals to initiate the deferral of electricity consumption to times of higher supply or lower demand—a process called “load shifting” (LS). In this paper, we employ the term “utility” to refer to an electric power company that engages in procuring and distributing electricity for sale to consumers. By allowing utilities to influence when certain appliances draw on electricity, consumers provide them with flexibility. Figure III.1-1 depicts the actors. One case example for LS would be postponing the charging process of a plug-in electric vehicle (PEV). Other conceivable LS examples can apply to household appliances with significant consumption, such as dish and clothes washers, dryers, electric heating, and air conditioning. Independent of the considered object for LS, the flexibility consumers provide bears economic value because it allows utilities to procure electricity when it is cheap on the electricity market (the "spot market" is the segment utilities make intraday trades on) and vice versa. As such, utilities gain the option to react to fluctuating spot market prices for electricity and realize a profit when shifting loads to times of a lower price. Other reasons such as saving the dispatch of expensive balancing power and lower strain on distribution grids may further motivate a utility to use LS.

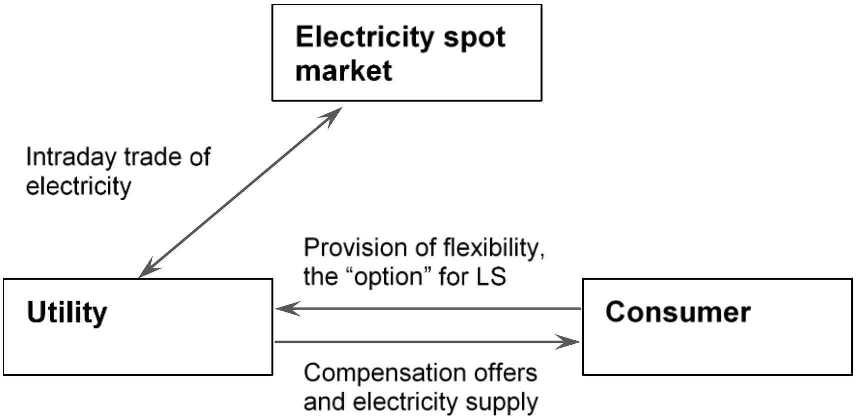

Figure III.1-1: Actors and relationships

Nonetheless, the tools to shape consumption provided through DR do come at a price. First, utilities need to invest in information systems (IS) that provide the transmission medium for signals and information, support decisions on when to shift loads, and initiate and control the process. Operating this infrastructure causes further costs. Second, utilities need to "buy" the flexibility consumers provide—they must offer consumers compensation for giving away the right to have their appliances at their complete disposal. An option would be for utilities to make consumers dynamic compensation offers in real time. As a result, to reach profitability, a utility needs methods to quantify the economic value of individual IS-enabled LS measures in consideration of electricity market information. In our vision, every time a consumer uses AMI to signal loads to be deferrable, utilities will be able to determine how much shifting them over the course of some hours is worth. Utilities will employ algorithms that will enable them to decide on LS initiation and duration. Intensified by the expansion of smart grids, AMI, and corresponding regulation, the opportunities for applying DR and deploying its capabilities for a sustainable energy transition will grow.

One can regard the flexibility a consumer offers to a utility as an option to shift loads; it enables the utility to decide whether to deliver the load immediately or later. From a temporal point of view, this flexibility is short term. It encompasses the number of hours (rather than days or weeks) the consumer is willing to wait for the load. In this paper, we focus on identifying a model capable of grasping this situation, the aforementioned "intraday" option in particular. Simultaneously, we note that electricity markets feature fluctuating prices, which imply an elevated risk. Therefore, we see the need to apply a dynamic investment methodology. To determine the option's value, established option valuation methods come into consideration. With electricity as a tangible, non-financial product, assessing the option's value by means of real options seems promising because real options analysis (ROA) captures flexibility of action and enables one to valuate dynamic investments under uncertainty by modeling volatility (Amram & Kulatilaka, 1999; Dixit & Pindyck, 1995; Trigeorgis, 1996).

From the overarching research objective described above, we derive our research question:

> **RQ:** How can one quantify the monetary value of IS-enabled, short-term flexibility in consumer demand for electricity using real options analysis?

Our research objective covers a relevant real-world problem because an answer could facilitate profitable LS decisions for utilities and help stabilize the equilibrium of electricity supply and demand. We apply design science research (DSR), which is "inherently a problem solving process" (Hevner, March, Park, & Ram, 2004). We pursue a corresponding approach to design an IS-enabled artifact that is applicable to various electricity markets worldwide, such as those in the United States and Europe. DSR seems to be a suitable approach for this undertaking because it provides a profound scheme for developing and communicating our artifact (Gregor & Hevner, 2013). We process electricity prices as the key information for our ROA. Thus, in many scenarios, our artifact needs to cope with a condition of uncertainty: LS comprises the course of some hours (i.e., intraday) during which price development is uncertain.

Real options theory features adequate model-theoretic requirements and numerous applications in IS research (Benaroch & Kauffman, 1999) and the energy sector (Ronn, 2003). Thus, we consider real options theory to be a rigorous kernel theory (in the terms of Gregor & Hevner, 2013) to underpin our artifact. In the course of our search process, we set up a stochastic model for electricity spot price development and, thereby, address a prerequisite of ROA (Ullrich, 2013). The model realistically captures seasonal price patterns and short-term effects of several hours and days but is straightforward to apply. We further design an algorithm that one can integrate into decision support systems (DSS) for short-term compensation offers. To that end, we model and evaluate a deferral option, which is an established type of a real option. For analytic assessment, we use the binomial tree model of Cox, Ross, and Rubinstein (1979), which guides LS initiation and duration. We further evaluate the artifact's effectiveness in a simulation based on historical data, which is a valid and rigorous design-evaluation method (Hevner et al., 2004). Finally, we attempt to generalize insights gained from our research and, thereby, underpin our research contribution.

This paper proceeds as follows: in Section III.1.2, we discuss related work. In Section III.1.3, we overview electricity markets (i.e. market instruments, market segments, and market differences). In Section III.1.4, we design our model. After formulating the problem setting, we present necessary assumptions and distinguish two cases: electricity procurement from hour-ahead markets or from real-time markets. For the former, we develop a simple valuation method for LS flexibility. With regard to real-time procurement, we develop an appropriate stochastic process based on a discretized version of a geometric Brownian motion to describe electricity spot market prices. We use this stochastic process to model and assess a deferral real option. Following a binomial tree approach, our ROA reveals a monetary value for IS-enabled flexibility in electricity consumption on real-time markets. We demonstrate this approach in Section III.1.5, describing how we evaluated our method for real-time markets. In Section III.1.6, we conclude the paper by discussing its contributions, addressing limitations, and presenting an outlook on further research.

III.1.2 Related Work

Paving the way for valuation of flexible loads in IS-supported DR is a contribution to "energy informatics" (EI). As a subfield of IS research, EI should apply "information systems thinking and skills to increase energy efficiency" (Watson, Boudreau, & Chen, 2010). We address this claim with our objective, which is to enhance the decision logic of IS for load control to increase the efficiency of electricity consumption and realize economic potential. Watson et al. (2010) suggest finding practical solutions to economize electricity consumption, which we develop in a valuation method applicable to short-term LS decisions. Goebel et al. (2014) and Strüker and van Dinther (2012) identify the need to quantify DR's economic potential. We focus on meeting this requirement to enable decisions on investment in technologies and compensations that facilitate LS on a level of consumer supply. We revise and extend our prior work (Fridgen, Häfner, König, & Sachs, 2014, 2015) by developing our real-time model's capability to account for short-term influences on electricity prices. Furthermore, we broaden our research by giving respect to hour-ahead markets to achieve a more general approach for utilities. Rigorously following DSR methodology, we extensively evaluate our artifact via simulation and sensitivity analyses and quantify the savings potential when shifting flexible loads under real circumstances.

Some scholars have determined the value of flexible loads by taking simulation approaches. Biegel, Hansen, Stoustrup, Andersen, and Harbo (2014) describe requirements for aligning flexible appliances with the electricity spot market. They also give an estimate of the cost and revenue, which depend on the magnitude of consumption. Vytelingum, Voice, Ramchurn, Rogers, and Jennings (2011) introduce an adaptive algorithm for micro-storage management in smart grids. Conducting simulations, they show that their approach can generate energy cost savings for an average consumer. Similarly, Rieger, Thummert, Fridgen, Kahlen, and Ketter (2016) determine potential electricity cost savings of up to 10 percent, which they attribute to their cooperative DR approach. Based on statistical data, Feuerriegel and Neumann (2014) derive an optimization problem for when to shift loads, which they then evaluate in a simulation. Goebel (2013) investigates a particular case of DR application: controlled charging of a fleet of plug-in electric vehicles. By simulation, the author finds that utilities with an intelligent charging schedule can secure a savings potential. Similarly, Kahlen and Ketter (2015) develop the algorithm "FleetPower" for balancing the power grid with a fleet of plug-in electric vehicles. Constituting a virtual power plant, the algorithm decides in real time whether to let cars for rent or to use them as an operating reserve for balancing the grid. The authors' simulation reveals that current developments in the energy sector enable "FleetPower" to generate significant savings. From a reproduction of household load profiles, Gottwalt, Ketter, Block, Collins, and Weinhardt (2011, p. 8172) conclude that "an individual household can expect rather low benefits of an investment in smart appliances". However, they consider the provided flexibility in electricity consumption highly valuable to utilities.

We go beyond the scope of these authors' works by developing an entire valuation rather than a pure simulation method. Serving as the kernel theory to our artifact, real options theory was derived from financial option valuation, which is a well-developed methodology. IS researchers have applied ROA in numerous cases (Benaroch & Kauffman, 1999; Ullrich, 2013). So far, in the energy sector, researchers have widely applied ROA to evaluate electricity-generation projects (Deng & Oren, 2003; Martinez-Cesena, Azzopardi, & Mutale, 2013; Ronn, 2003). Converging to our objective, some scholars have argued that research should use the capabilities of real options to assess the monetary value of IS-enabled flexibility in electricity consumption with respect to uncertainty in electricity prices. Sezgen, Goldman, and Krishnarao (2007, p. 108) stress the need to quantify "the economic value of investments in technologies that manage electricity demand in response to changing energy prices". We consider Sezgen et al.'s (2007) method for ROA an important contribution. However, their model suits thermal energy storage technologies and cannot capture intraday flexibility. Sezgen et al. (2007) leave such flexibility to follow-up work. Oren (2001) designs a real options approach to hedge against price risk in the electricity spot market. He concludes that the unadjusted model does not suffice to replicate electricity spot price development and leaves the formation of more realistic models to further research.

Both approaches cannot evaluate short-term LS realized through IS, which is a real-world use case and integral part of our research question. Nonetheless, similarly to the papers of Sezgen et al. (2007) and Oren (2001), our artifact sets on electricity prices, which means we need to consider their stochastic price movement to derive an appropriate valuation method. While Sezgen et al. (2007) and Oren (2001) build their models based on the assumption of a regular geometric Brownian motion process for electricity prices, our spot price model incorporates realistic time-dependent mean price levels and mean-reverting properties to enable short-term LS decisions.

Beyond the literature on real options modeling of electricity consumption, other scholars have also studied the prerequisite to stochastically model electricity spot market prices. Coulon, Powell, and Sircar (2013) develop a model that accounts for the complex relationship between electricity spot market prices and underlying factors. In particular, Coulon et al. (2013) capture three stochastic factors (gas price, load and available capacity) to account for electricity price dynamics and a switching regime for modeling price spikes. While this approach seems to suit to hedge portfolios of generating assets and load-serving obligations, it is too complex for our purpose in that we only need to estimate future price developments and not their ultimate causes. Fanone, Gamba, and Prokopczuk (2013) build a non-Gaussian stochastic process for day-ahead electricity prices. Using data from the European electricity exchange, the authors model current developments in the German day-ahead market by considering negative electricity prices. Huisman, Huurman, and Mahieu (2007) introduce a panel model for hourly electricity prices in day-ahead markets. They build a stochastic process that describes price differences while considering uncertainty with hour-specific mean price levels and mean-reverting properties. However, since the authors model panels of 24 prices that simultaneously result from day-ahead auctions, the single prices are not an intraday movement or a time series. A set 24-hour pricing panel is not appropriate for our purposes. Other approaches to model electricity price development by stochastic means include Weron, Bierbrauer, and Trück (2004), Deng and Jiang (2005), Kim and Powell (2011), Schneider (2012), and Benth, Klüppelberg, Müller, and Vos (2014). After analyzing these studies, we concluded that no included approach met the requirements for our research question without overstepping bearable complexity for our valuation method. Since we focus on valuating short-term consumption flexibility in a comprehensible and assessable way, we built our own appropriate process for electricity price movements.

III.1.3 Overview of Short-term Electricity Markets

III.1.3.1 Market Instruments

Utilities secure medium- to long-term supply for base and, partially, peak loads far in advance through generation capacity, bilateral supply contracts, and/or acquired futures contracts. Nonetheless, ultimately, they need to bring fluctuating demand in line with supply in the short term. Accordingly, for LS scenarios, short-term market instruments with a timeframe similar to the granted flexibility are relevant to consider. In this section, we describe the structures we observe in European and North American power systems. However, not all markets feature every market instrument.

Utilities balance their short-term demand and supply actively with physically delivered electricity market instruments and passively with the help of external "balancing power" the system operator controls (Biegel et al., 2014). Figure III.1-2 illustrates the typical instruments available for adjusting to consumption in the short term.

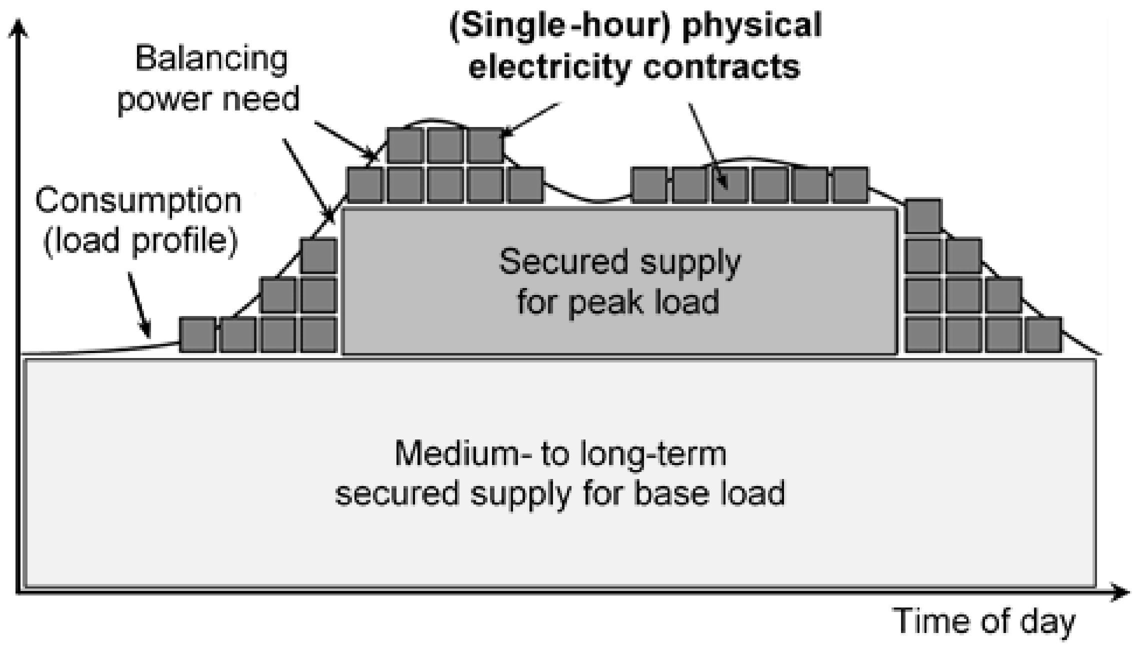

Figure III.1-2: Market instruments for adjustment to consumption

Dispatching balancing power is costly, much more expensive than electricity spot market prices (Strüker & van Dinther, 2012). Therefore, actively adjusting power to deal with fluctuating consumption via purchasing a sufficient volume of physical electricity contracts is the preferred means for utilities in need for additional electricity supply and our subject of research. “Physicial electricity contracts” are standardized contracts on the physical delivery of a certain amount of electricity over a specified period. Further, “actual consumption or production as part of contract fulfillment” (Benth, Saltyte Benth, & Koekebakker, 2008) characterize such physical electricity contracts.

Utilities, just like other market participants, commonly trade physical electricity contracts on electricity spot markets close to the time of delivery. Integrating renewable energy sources into the grid increases utilities’ demand for spot market flexibility due to these sources’ volatile electricity production. This demand is expressed in rising trading volumes on electricity spot markets (e.g., EPEX SPOT, 2015). We focus our research to the perspective of a utility that conducts intraday trades on the spot market to procure additional physical electricity contracts in order to balance its short-term demand and supply. Whenever such a utility seizes flexibility to shift loads to another period, it secures savings as high as the difference in spot market prices. In other scenarios, that utility could possibly offer gained capacity on the spot market or on the market for balancing power with higher margins.

However, because this latter market type is complex, difficult to predict, and differing between countries, taking a close look at it would exceed this paper's scope.

The small flexibility of electricity production, restricted by technical and regulatory constraints, can even cause negative spot prices for the physical electricity contracts (Schneider, 2012). At times, for example, a surge in wind power may conincide with little demand for electricity or slow reduction of conventional power plant capacity. The regulatory framework in Germany, which has given electricity generated from renewable sources feed-in guarantees and precedence over conventional sources, is an origin to such issues (Frondel, Ritter, Schmidt, & Vance, 2010). Additionally, the share of renewable energy sources in Germany's electricity production has risen constantly (Kiesel, 2015) and, thus, caused increasing price volatilities (Nicolosi & Fürsch, 2009). Therefore, negative prices have appeared more frequently in Germany than in other markets. Researchers expect negative prices to occur more frequently in the future (Brijs, de Vos, de Jonghe, & Belmans, 2015). DR is a powerful response to negative electricity prices. First, procuring physical electricity contracts at times of negative prices will prove especially valuable for load delivery. Second, IS-enabled LS can help bring electricity consumption into line with fluctuating production, which will counteract excess supply. Nonetheless, the extent of the increase in non-positive electricity spot prices remains uncertain. In fact, due to regulatory frameworks, it could remain a phenomenon limited to few electricity markets, such as the German-Austrian market. Our spot market data analysis suggested that, so far, negative spot prices have proven to be exceptions. Hence, we do not work on integrating them in this paper's artifact. As such, we note that the value derived in our model is set on the lower bound of DR's potential.

III.1.3.2 Market Segments

Utilities trade physical electricity contracts sequentially on three interconnected types of short-term markets: day-ahead, hour-ahead, and real-time electricity markets (Umutlu, Dorsman, & Telatar, 2011). Spot markets, which in our definition (corresponding to Wilson, 2002) signify the intraday market, often comprise both hour-ahead and real-time segments; in other environments, they are limited to the latter.

Day-ahead and hour-ahead markets are, technically speaking, forward markets in which participants trade electricity contracts in advance for specific times of the day. On a "day-ahead market", two-sided blind auction mechanisms determine the price levels for physical electricity contracts on electricity delivery in the following day's timeframe (between midnight and midnight). Supplying and demanding parties place commitment bids (each of which comprise load volume and price) regarding single hours or blocks of hours of the following day. After the day-ahead market closes for submissions, the market operator integrates bids into intersecting supply and demand curves, which results in a panel of electricity contract prices for each hour of the following day. To quote blocks of hours, one simply averages the respective single-hour prices. That panel provides the starting point for the electricity spot markets and power transmission planning. Spot markets enable participants to continuously trade electricity contracts in shorter periods before delivery. This way, in reaction to prediction errors or other deviations from their plans, market participants can further balance their schedules by selling or purchasing replacement energy.

The "hour-ahead market" bridges the gap between the end of the auction on the day before delivery and the actual delivery hour the contractors have agreed on. Participants can purchase physical electricity contracts for any future delivery hour of the day, starting shortly after the market operator has quoted the day-ahead prices. Since one can purchase contracts in advance without exposure to uncertain price movements, this form of procurement mitigates risk. The market design may include "gate closure", indicating that a contract's trade on the hour-ahead market is to terminate at a fixed time before the delivery hour.

The "real-time market" is the segment for settling remaining deviations from day-ahead or hour-ahead schedules as electricity consumption fluctuates throughout the day. Participants trade electricity for immediate or the earliest possible delivery. Therefore, considering marginal costs, they "can bid the prices they require (offer) to increase (decrease) their generation, or decrease (increase) their consumption" (Umutlu et al., 2011, p. 113).

As we mention above, we focus on intraday (i.e., spot) markets for procuring electricity, which are suitable for modeling short-term flexibility in electricity consumption. If hour-ahead markets are available, they provide the first option to procure electricity in advance at reduced exposure to price risk. Procuring electricity from the real-time markets close to the time of consumption is the second option.

III.1.3.3 Market Differences

Hour-ahead markets exist in most deregulated European power systems but generally not in U.S. power systems. An exception is California, where the California Independent System Operator provides an hour-ahead market segment. Power system operators for the northeastern states of the US (ISO-NE and PJM) and for Texas (ERCOT), for instance, operate real-time instead of hour-ahead markets. The three largest European spot markets incorporate hour-ahead segments, each of which allows participants to trade electricity across several countries' power grids: the Amsterdam Power Exchange (APX) for the Netherlands, United Kingdom, and—with the closely associated market Belpex—Belgium; the European Power Exchange (EPEX SPOT) for France, Germany, Austria, and Switzerland; and Nord Pool Spot for the Scandinavian and Baltic countries.

In these hour-ahead markets, participants typically trade physical electricity contracts in hourly units. Hence, the market introduces 24 new single-hour electricity contracts daily following a day-ahead auction. For select countries, participants can also purchase finer granularities on APX (30-minute units for UK), Nord Pool Spot, and EPEX SPOT (15-minute units for Austria, Germany and Switzerland). At all times, the next available electricity contract fulfills the function of real-time trade because it accomplishes earliest possible load delivery. Therefore, in European hour-ahead markets, one can compare the final spot price for an electricity contract at market closure to a real-time price, although there is no designated real-time market before the spot market closes and balancing power trade remains. For reasons of data availability, we study final spot prices for electricity contracts from EPEX SPOT's hour-ahead market, which serve as a substitute for real-time prices.

III.1.4 Model

III.1.4.1 Problem Setting

We use the electricity markets and market instruments we describe in Section III.1.3 as the basis for evaluating IS-enabled, short-term flexibility in electricity consumption. Utilities have three reasons in particular to get to know the monetary value of this flexibility before taking DR actions. First, they must cover technological investments such as AMI and operating costs for IS infrastructure, administration, and consumer relations. Second, they have to compensate consumers for releasing some of their flexibility. Third, utilities should monetarily compensate themselves to reward the business hazards of DR. For instance, DR involves risks about general consumers' acceptance, opportunity costs through expended capital and operational risks such as technical breakdowns.

To summarize, a utility needs a DR business case that provides a basis to estimate cash flows from LS. Because we expect that AMI will enable several business cases for utilities besides

DR (e.g., deducing accurate load profiles to improve generation capacity and power transmission planning), we are convinced that more than one single case will justify necessary investments and operating costs for IS infrastructure.

III.1.4.2 Assumptions and Case Distinction

We consider single-hour physical electricity contracts with our valuation method because single-hour contracts are the most common unit of short-term electricity trade. Such a contract comprises the delivery of a certain amount of electricity during a 60-minute period starting on the hour. To deliver loads, utilities procure one or several of such electricity contracts. If a utility needs more than one single-hour contract due to a multi-hour consumption pattern or a high amount of required electricity, the utility may procure all electricity contracts at the same time.

Assumption 1: A utility purchases all single-hour electricity contracts necessary to deliver a load at once.

One can transfer our model to half- or quarter-hourly contracts without losing its meaning. Nevertheless, we assume a common basis of single-hour electricity contracts for generality. Furthermore, we need to assume that the utility can expend electricity contracts as purchased from the markets without transmission restrictions.

Assumption 2: Utilities face no physical restrictions in procuring and delivering electricity.

Because procuring electricity from both hour-ahead and real-time markets pertains to our research question, we develop a method to accommodate both cases. Hour-ahead markets enable one to procure electricity contracts in advance for hours during the LS window. Because procuring electricity contracts in advance reduces price risk compared to the real-time market, utilities ought to prefer procuring electricity on hour-ahead markets. Therefore, we distinguish between the two markets based on whether a utility has access to an hour-ahead market. We discuss hour-ahead procurement in Section III.1.4.3. When an hour-ahead market does not exist, utilities need to procure electricity from the real-time market—a case more complex to evaluate. We discuss and formalize an appropriate deferral real option in Section III.1.4.4. A third case is that the LS window spans more hours than electricity contracts are available for hour-ahead procurement. We discuss this case in Section III.1.4.5.

Figure III.1-3 summarizes the three cases. It depicts an example of a LS decision that a utility has to make just before 1 p.m. In the first two cases, the LS window spans until the evening. Load delivery may first possibly start at 1 p.m. Whether an hour-ahead market is available to the utility determines hour-ahead or real-time procurement. In a third scenario, the LS window spans until the next morning, which means some single-hour contracts are unavailable for hour-ahead procurement until a day-ahead auction yields the panel of electricity prices for the next day (which is, for example, at 3 p.m. on EPEX SPOT). In Figure III.1-3, we depict single-hour contracts as squares (similarly to Figure III.1-2); dark-shaded squares indicate example contracts a utility might decide to procure.

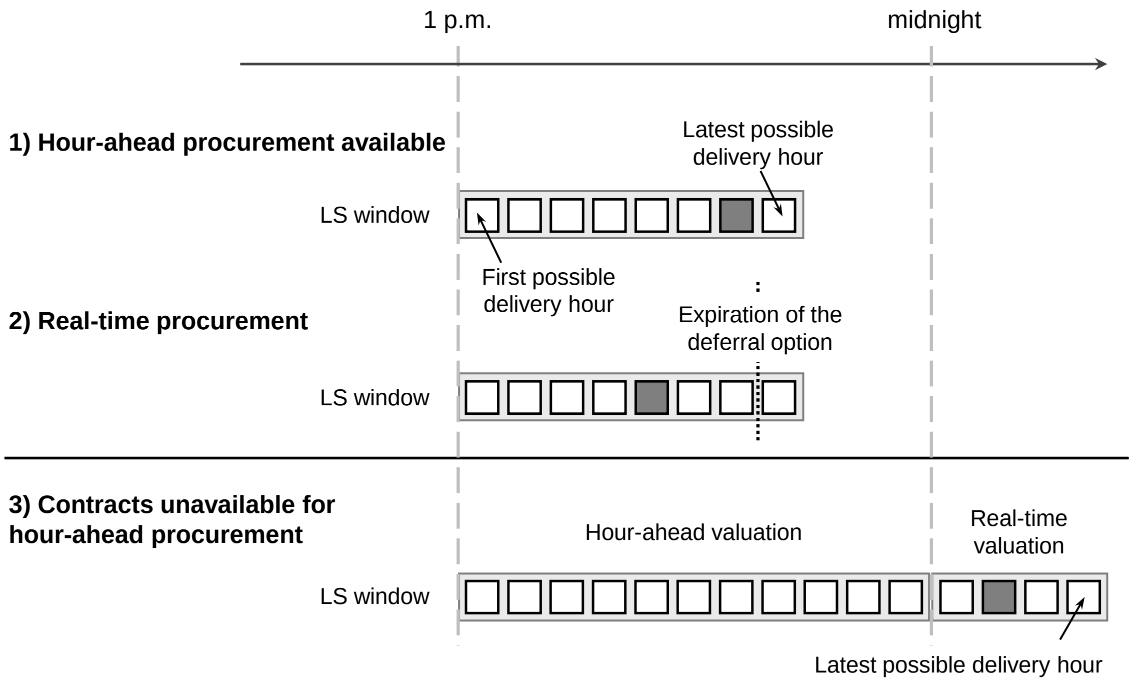

Figure III.1-3: Valuation with hour-ahead procurement available

In considering hour-ahead procurement possibilities, we broaden the approach applied in our previous work (Fridgen et al., 2015). A consumer that offers flexibility in when they consume electricity still expects the utility to start delivering a load not later than a certain time. This specified time is T hours from the first possible delivery hour, which indicates LS's maximum duration. $t = 0$ is the beginning of the next hour. Ceteris paribus, the utility has no spare electricity on hand, which leaves it with no option to instantly deliver a load apart from choosing balancing power. The next available single-hour contract is the utility's earliest possibility to procure necessary electricity.

Assumption 3: Delivering a load can begin on the next hour at the earliest.

We further assume that a utility that intends to adjust its supply situation can procure replacement energy from the hour-ahead market up to the beginning of the hour it needs to deliver a load. The assumed situation comes close to reality at APX, on which a utility may procure physical electricity contracts up to five minutes before beginning to deliver a load. In other markets that terminate trade earlier (gate closure), a utility might respond by purchasing extra electricity contracts in anticipation of additional loads coming in after the gate closes. Future research could integrate such an approach into our valuation method.

Assumption 4: In hour-ahead markets, electricity contracts are available for purchase up to zero minutes before the beginning of the delivery hour (technically speaking, without early gate closure).

Just before $t = 0$, one can observe prices for several single-hour electricity contracts in the LS window on the hour-ahead market. First, one can observe the spot price S_0^0 for delivery beginning in $t = 0$ during the first possible delivery hour. Second, one can observe a number of prices S_0^t for the following hours' contracts. Henceforth, we notate the time one observes a spot price in subscript and the delivery time in superscript.

If the utility can deliver the required load over the course of one hour, it selects the cheapest single-hour contract available from the hour-ahead market in $t = 0$ to schedule load delivery and can, thereby, mitigate its exposure to price changes. In its decision, the utility follows a minimum consideration:

$$\min\{S_0^0, \dots, S_0^T\} = \min_{t \in \{0,\dots,T\}} \{S_0^t\} \tag{1}$$

In the event that the utility needs to deliver the load over the course of more than one hour, it can adjust the optimal procedure as follows. The adjustment depends on whether the utility may pause and split the delivery between non-consecutive hours. If doing so is possible, the utility simply selects the lowest-priced electricity contracts during the LS window in the appropriate quantity, which is similar to Equation 1. If the utility must deliver the load uninterruptedly, it should regard the average prices of sets of consecutive single-hour contracts. The utility then selects the set of consecutive contracts with the lowest average price again according to Equation 1.

We define A_x as a set of all combinations of x consecutive delivery hours between $t = 0$ and $t = T$ (respecting constraints). $a_{x,t^*} \in A_x$ are the elements of A_x, where $t^* \in [0, T]$ denotes the beginning of delivery. We need to minimize the price sum of these delivery hour combinations:

$$\min_{t^*}\left\{\sum_{t\in[t^*,t^*+x-1]} S_0^t\right\} \tag{2}$$

For example, if a utility has to initiate a load delivery between the beginning of the next hour ($t = 0$) and three hours in the future ($T = 3$) for the duration of two consecutive hours, then we have $A_x = \{a_{2,0}, a_{2,1}, a_{2,2}, a_{2,3}\}$. Therefore, we search the minimum sum of two consecutive prices, that is $\min\{(S_0^0 + S_0^1), (S_0^1 + S_0^2), (S_0^2 + S_0^3), (S_0^3 + S_0^4)\}$.

We can expect the utility to realize a monetary advantage through LS, which we—for simplicity—present in the single-hour delivery case. Without flexibility, the utility would need to pay the next hour's spot price S_0^0. From an ex ante perspective, the utility's decision on LS yields a monetary advantage V. V is the difference of the minimum procurement price according to Equation 1 and the next hour's spot price S_0^0:

$$V = \max\{S_0^0 - S_0^0, \dots, S_0^0 - S_0^T\} = \max\{0, \dots, S_0^0 - S_0^T\} \tag{3}$$

This monetary advantage is the value of LS flexibility in the hour-ahead electricity market. In a generalized formula, we obtain:

$$V = \max_{t\in\{0,\dots,T\}}\{S_0^0 - S_0^t\} \tag{4}$$

III.1.4.3 Valuation with Real-time Procurement

III.1.4.3.1. Spot Market Data Analysis

Power systems with real-time instead of hour-ahead markets require one to acknowledge the uncertainty in how intraday prices develop. With real options theory serving as the kernel theory to our artifact, we model a utility's flexibility to shift loads as a deferral option. Single-hour electricity contracts constitute the underlying asset to this real option (in the following: "underlying"). To analytically assess the deferral option's value, one requires a stochastic process that appropriately depicts the uncertainty in the underlying price's development (Benaroch & Kauffman, 1999; Ullrich, 2013). We developed a stochastic process and a valuation model for real-time markets in previous work (Fridgen et al., 2014, 2015). Because this model cannot account for short-term influences on spot prices, we develop an extension in this paper to closer depict spot market reality in the stochastic process.

To determine what real-world factors our stochastic process should respect, we study a time series of historical spot market price data from the German-Austrian market area of EPEX SPOT. The high and increasing capacity of renewable energy sources in this market (Würzburg, Labandeira, & Linares, 2013) is groundbreaking and will be exemplary for other electricity markets in the future. In 2013, the trading volume on the EPEX SPOT intraday markets amounted to 19.7 TWh for the German-Austrian market area (EPEX SPOT, 2015). In comparison, the gross national electricity consumption amounted to 599.4 TWh in Germany (Kiesel, 2015) and 64.5 TWh in Austria (Bundesministerium für Wissenschaft, Forschung und Wirtschaft, 2015). Hence, the German-Austrian intraday market held a 3.0 percent market share in 2013. This share is notable considering that utilities prefer medium- to long-term commitments to secure the major share of electricity supply (which is non-responsive to DR efforts). Also, this share is rapidly increasing: EPEX SPOT's latest numbers (as of 2015) indicate a trading volume of 26.4 TWh in 2014, which equals a 33.9 percent growth that one can attribute to the transition of electricity generation to renewable energy sources (EPEX SPOT, 2015). Rising trading volume in the intraday market and its location in the core of the interconnected European power grid, which may influence other markets in the future (Würzburg et al., 2013), make the German-Austrian market an interesting object to study.

Market participants trade electricity for the German and Austrian grid in one shared market separate from the other market areas. Quoted in Euro per megawatt hour (€/MWh), single-hour physical electricity contracts are the traded objects. Spot prices are initially the outcome of auctions on the day-ahead market and, thereafter, are impacted by intraday trade up to 15 minutes before delivery.

We retrieved our data set from Thomson Reuters Datastream. Our query yielded final spot market prices for 24 hours on weekdays. To be able to measure sensitivity of DR savings potential to seasonality and historical reference timespans, we conducted statistical analyses on various years (10, 5, 3, and 1) of spot market prices before and including the boundary date 31 May 2014. Because electricity production and consumption are typically linked to the season (Benth et al., 2014), we distinguished between summer, winter, and intermediate seasons. Spring and autumn jointly make up the intermediate season because they are comparable in terms of climatic conditions. From the obtained historical data, we established an hour-to-hour series of electricity spot market prices.

	Summer	Winter	Intermediate	Overall
Chronology				
Time intervals	Jun–Aug	Dec–Feb	Mar-May, Sep-Nov	1 Jun 2011- 31 May 2014
Total days	276	271	549	1,096
Spot prices				
No. of observations	4,731	4,658	9,404	18,793
No. of positive values	4,731	4,599	9,394	18,724
Mean (€/MWh)	45.51	43.98	44.43	44.95
Std. deviation (€/MWh)	12.32	23.58	15.39	15.55
Maximum (€/MWh)	130.27	210.00	121.97	210.00
Minimum (€/MWh)	3.02	-221.99	-49.06	-221.99
Hour-to-hour returns				
No. of returns	4,731	4,587	9,389	18,707
Mean	-0.0001	0.0031	-0.0003	0.0006
Standard deviation	0.1346	0.3184	0.1929	0.2193

Table III.1-1: Descriptive statistics for time series of spot market prices

Table III.1-1 depicts the descriptive statistics for the three-year period. This period's boundary dates encompassed three summers (Jun-Aug; 2011-2013), three winters (Dec-Feb; 2011/12-2013/14), and six intermediate seasons (Mar-May, Sep-Nov; 2011-2014) in the meteorological sense. Over all regarded periods, we observed similar daily patterns in spot price movement. Nonetheless, between the ten- and one-year periods, the overall price means continuously decreased from 48.90 to 39.11 €/MWh mostly due to the rising share of renewable energy sources in electricity production. More and more energy producers integrating renewable energy sources into the grid have impacted electricity market prices (International Energy Agency, 2013). For instance, since 2011, renewable sources have contributed electricity equal to more than a fifth of gross consumption in Germany. To account for this significant trend, we should generally focus on analyzing data over a shorter time series. However, the regarded time series should be long enough to eliminate non-representative influences.

The special case of negative spot prices occurred rarely: 69 hourly prices, an insignificant share of 0.37 percent of our data, valued less or equal to zero. Therefore, an assumption to exclude those negative prices hardly affected our data set.

Assumption 5: The modelled real-time market allows no negative spot prices.

This assumption is technically necessary to apply ROA since traditional option pricing models are designed for capital markets. On capital markets, negative prices cannot exist due to investors' limited liability (i.e., the investors may lose all they have invested but not more than that). In our context, this simplifying assumption will not harm since negative spot prices would only further increase LS savings.

One can expect electricity spot prices to drift toward a season-specific, long-term mean (so-called "mean reversion", Benth et al., 2014). To form seasonal and time-specific expectations, we determined average daily price curves (see Figure III.1-4). These price curves are representative of days in winter, summer, and intermediate seasons in accordance with the historical data from EPEX SPOT. Following typical human electricity consumption patterns, each price curve's minimum is in the morning hours, in the spot price for electricity contracts for delivery from 4 a.m. onward. A sharp increase during the morning hours is typical until the price curves reach a plateau around 8 a.m. The price curves tend to decline in the afternoon. In the darker seasons, a substantially elevated price level occurs between 5 p.m. and 9 p.m. From 10 p.m. on, price curves for all seasons take a steady downward slope throughout the night.

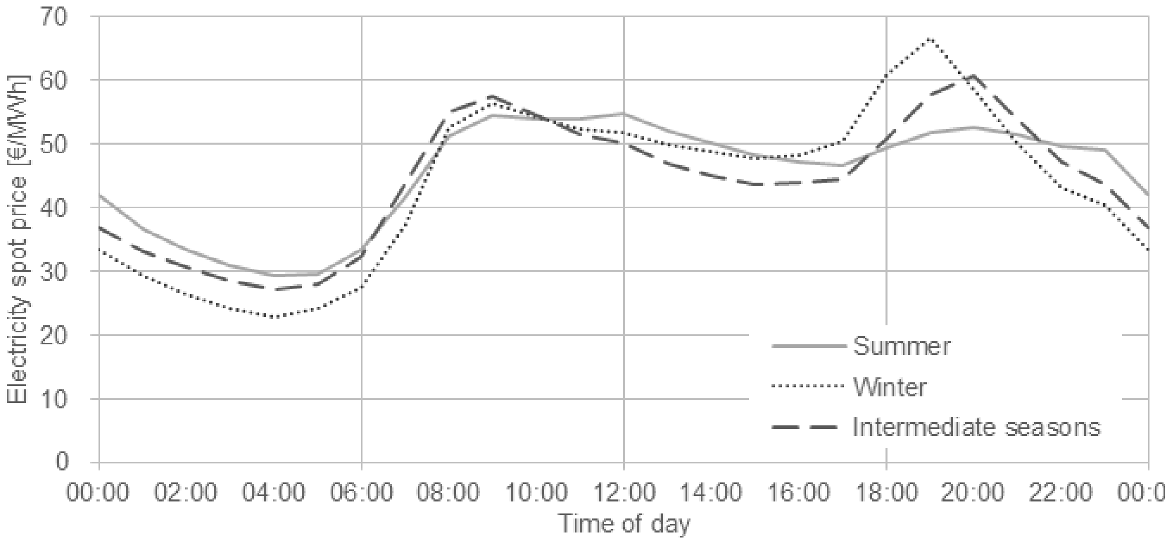

Figure III.1-4: Historical average daily price curves

We equip our stochastic process to follow the described patterns. In particular, we transformed the spot price series into geometrical hour-to-hour returns. “Returns”, a term we adopted from financial markets, depict the change (slope) in a price curve, which provides a measure for movement in electricity spot prices from hour to hour. We defined geometrical returns $\mathrm{R(t)}$ as follows, with $\mathrm{S(t)}$ being the observed spot price at hour t and $\mathrm{t-1}$ indicating the previous hour:

$$\mathrm{R(t)} = \lg\frac{\mathrm{S(t)}}{\mathrm{S(t-1)}} \tag{5}$$

Because we excluded negative and zero spot price values from the data set, we computed geometrical returns only on positive spot prices. Table III.1-1 also depicts descriptive statistics for these hour-to-hour returns. Standard deviations, measures for “volatility” as we phrase it in the following, provide an indication of spot price fluctuations depending on the season. Winter featured the highest volatility of returns. This volatility documents the variability in demand or supply from hour to hour, which utilities and grid operators need to balance.

III.1.4.3.2. Adjustment of a Geometric Brownian Motion Process

A stochastic process to depict the spot price development of hourly physical electricity contracts should incorporate mean reversion. The “square-root diffusion process” (Cox, Ingersoll, & Ross, 1985) and the “Ornstein–Uhlenbeck process” (Uhlenbeck & Ornstein, 1930; Vasicek, 1977) are common mean-reverting processes for continuous-time valuation. Both require constant mean and volatility, which would not be adequate for an intraday approach because the long-term means and volatilities of single-hour contract spot prices differ considerably from hour to hour. In addition, continuous-time valuation cannot adequately consider trade in hourly increments. As such, one cannot use existing mean-reverting processes to replicate short-term spot price movement in volatile electricity markets. Instead, from an intraday perspective, a discrete-time model suffices to simulate electricity prices.

To reach an appropriate stochastic process, we build a discretized version of a “geometric Brownian motion” (GBM). A GBM is a simple stochastic process that describes deterministic and uncertain changes of an underlying value - in our case, the electricity spot price S - as a function of time t. The term $\mu\mathrm{S(t)}$, also called “drift”, describes the value change of the process during one time step (here, the expected spot price change in one hour). We use $\mu \geq$

0 as the expected relative return to express the drift as a fraction of its current value $S(t)$. The term $\sigma S(t)dW(t)$ describes uncertain changes. In this construct, σ specifies the volatility of returns, which controls for the influence of coincidence. $W(t)$, a so-called "Wiener process" (Merton, 1997), models normally distributed returns. We assume a Gaussian distribution for the previously described spot price returns, which their distribution approximately resembles.

> Assumption 6: The relative changes in electricity spot prices (returns) are normally distributed.

For rigor, we apply this assumption, which is common in financial markets. Finance research usually assumes Gaussian distribution, although some papers have shown that the assumption does not always hold true (e.g., Fama, 1965). Similarly, researchers have repeatedly used this assumption in electricity markets (Hellström, Lundgren, & Yu, 2012; Huisman & Mahieu, 2003). The assumption helps to depict reality, which it comes close to, even though electricity price distributions at times are not Gaussian and instead feature heavy tails (Mayer, Schmid, & Weber, 2015; Weron, 2009). In the light of our results, we consider this limitation acceptable.

In summary, the following equation describes the GBM of $S(t)$:

$$dS(t) = \mu S(t)dt + \sigma S(t)dW(t) \tag{6}$$

Because we apply a discrete-time model, we can use single hourly increments. As a result, one can regard the value change in spot prices S as an absolute difference, and the returns of the Wiener process follow a standard normal distribution $N(0,1)$:

$$dt = 1, \quad dS(t) = S(t+1) - S(t), \quad dW(t) = N(0,1) \tag{7}$$

Altogether, the following equation describes our discretized version of a GBM:

$$S(t+1) = S(t)(1+\mu) + \sigma S(t)N(0,1) \tag{8}$$

We sought to size the process appropriately so that it would cope with significant intraday patterns in the historical spot price data. Therefore, we set the drift on every hour so that the process reverts toward the long-term mean until the next discrete time step $t+1$. Hence, continuing the expected relative return μ introduced above, $\mu(t)$ is the time-dependent expected relative return of the process. One determines it by using the long-term mean of $S(t+1)$; namely, $\dot{S}(t+1)$. We scale this long-term mean with α, an adjustment factor that allows the stochastic process to account for short-term effects. This scaling is reasonable since temporary and unexpected environmental conditions, such as fluctuations of current electricity demand and production, events (e.g., soccer world cup finals), holidays, or weather, can influence the development of electricity spot prices. If several hours' electricity prices on a specific day are far above their long-term mean, for example, this pattern will likely continue in the next hours. Therefore, the integration of α into our model is a major extension compared to the model from our prior work (Fridgen et al., 2015). As a factor for adjusting the mean-reversion speed of $\mu(t)$, we further introduce $\theta \in [0,1]$:

$$\mu(t) = \theta \frac{\alpha \dot{S}(t+1) - S(t)}{S(t)} \tag{9}$$

Assume $\theta = 1$; doing so sets the expected relative return such that the forecasted value for the next hour's electricity spot price equals its adjusted historical mean at that hour, which signifies complete reversion to the adjusted mean. Accordingly, $\theta = 0$ implies no reversion toward the mean whereby only uncertainty drives the process. Uncertainty depends on a standard Wiener process and on the volatility of hour-to-hour returns, which we obtained from the historical data in accordance with Equation 5. Due to large differences in historical volatility, one should consider the time of day for this parameter, too. Thus, our model considers average, time-dependent historical returns and time-dependent historical volatilities $\dot{\sigma}(t)$:

$$S(t+1) = S(t) + \theta\left(\alpha \dot{S}(t+1) - S(t)\right) + \dot{\sigma}(t) S(t) N(0,1) \tag{10}$$

In summary, the spot price expected for the next hour equals the current hour's spot price, which converges toward the adjusted long-term mean for the next hour (speed-weighted through the mean-reversion factor) and integrates a standard normally distributed source of uncertainty. At time $t+1$, one has to adjust historical return and volatility to the new time of day, which technically creates a new discretized GBM. As a result, we can compare the stochastic process over several discrete time steps to a chain of single-period stochastic processes (with mean reversion and volatility constant for one time step). We refer to this chain as "modified GBM".

Figure III.1-5 illustrates the resulting process chain through a randomly generated curve for a summer day, compares it to the respective historical average price curve, and illustrates the influence of θ. The diagram demonstrates how simulated spot prices evolve stochastically around long-term means (for simplicity, we neutralize the adjustment of long-term means here; i.e., $\alpha = 1$). The law of large numbers indicates that a simulation that averages a sufficient quantity of randomly generated modified GBM should yield the initial average price curves. Our simulation confirms that the modified GBM approximates to historical data. This observation indicates that our process provides a realistic base for a subsequent monetary valuation of consumption flexibility.

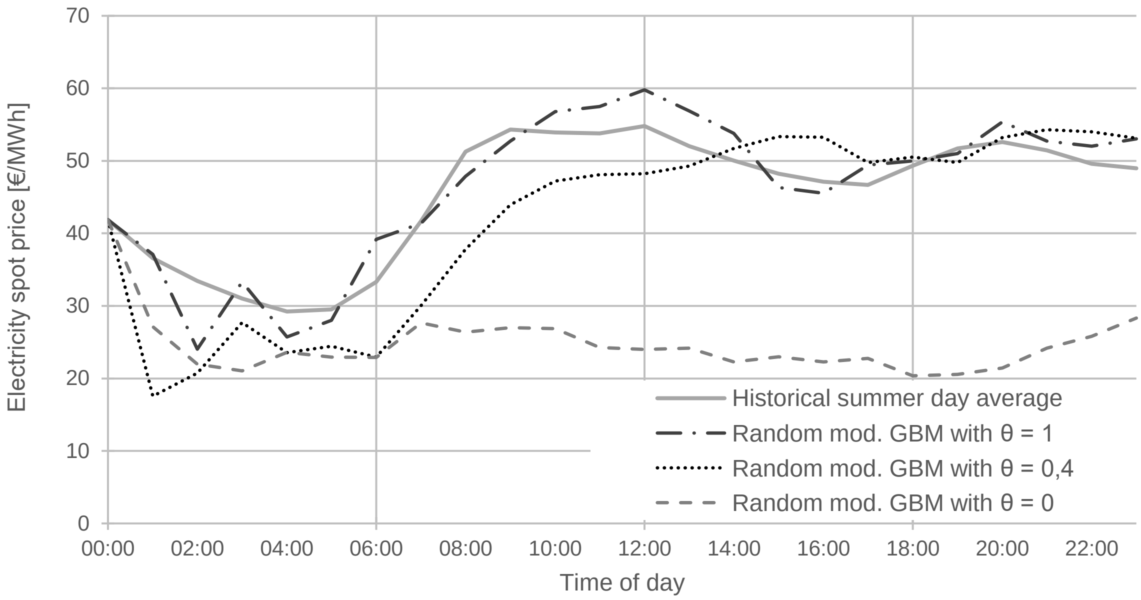

Figure III.1-5: Summer day simulation of modified GBM with different mean-reversion speeds

III.1.4.3.3. Binomial Tree for Spot Price Prediction

We derive a binomial expression of our modified GBM in Equation 10 to assess a deferral option's value. Cox et al.'s (1979) traditional binomial tree model approximately simulates discrete-time movements of an arbitrary standard GBM (Rostek, 2009). It is a common approach for valuing discrete options and suits ROA (Hilhorst, Ribbers, van Heck, & Smits, 2008). As found in the traditional binomial tree model, $t = 0$ is our ROA's starting point, a point in time at which the algorithm has to make a decision about whether to initiate LS. $S(0)$ is the spot price observable on the electricity market at this time; thus, it is known. For any following point in time, spot prices are unknown. The tree forks at each discrete point in time t, which reflects the uncertainty in electricity spot price movement.

In each node, spot price movement may continue in either an upward or a downward direction. We define $u_t \geq 1$ and $d_t \leq 1$ (with $u_t d_t = 1$) as the time-dependent factors for up and down movements of the electricity spot price $S(t)$, respectively. Upward or downward movements are not equally likely: p_t depicts the time-dependent probability that the process will move into the upside scenario. In our case, this parameter indicates the probability that the electricity spot price will increase in the next hour. $1 - p_t$ is the time-dependent probability for the downside scenario.

Assumption 7: Utilities are risk-neutral in their procurement decisions.

Under the assumption of risk-neutrality, Cox et al. (1979) obtain the following equations:

$$u_t = e^{\dot{\sigma}(t)\sqrt{\Delta t}},\ d_t = e^{-\dot{\sigma}(t)\sqrt{\Delta t}},\ p_t = \frac{e^{r_f \Delta t} - d_t}{u_t - d_t} \tag{11}$$

Δt equals 1 for single-hour time steps. Cox et al. (1979) use the parameters in Equation 11 to derive two possible upcoming prices for $S(t)$: $S_u(t+1) = S(t)u_t$ and $S_d(t+1) = S(t)d_t$. Since this model builds on the assumptions of risk neutrality and no arbitrage, it allows drifting only in form of the risk-free interest rate r_f (with $u_t > 1 + r_f > d_t$). This restriction is reasonable because Cox et al. (1979) developed their model for pricing financial options in complete and perfect capital markets where arbitrage opportunities would disappear infinitely fast. However, participants in electricity markets are in large part not able to use arbitrage opportunities since utilities usually have to get and deliver electricity exactly at the time of (exogenous) demand. This difference between financial and electricity markets justifies the existence of a mean-reversion property in electricity markets and raises the question of how we can consider mean-reversion in the binomial model without endangering the validity of the given formulas. We modify the traditional model in two aspects. First, we set $r_f = 0$ since interest drilled down to one hour is insignificantly low. Second, we treat our mean-reverting property (drift) similar to discrete dividend payments in capital markets, which is a valid application of the traditional model. Indeed, anticipating a discrete future payment in the world of securities is comparable to anticipating expected price movements in a risk-neutral electricity market.

To summarize, we add the discrete mean reversion to the two possible upcoming prices, an approach that resembles discrete dividend payments in the original model of Cox et al. (1979). Initially observing $S(0)$ in $t = 0$, we obtain the following period's spot prices $S(1)$:

$$S_u(1) = S(0)u_0 + \theta\left(\alpha\dot{S}(1) - S(0)\right),\ \ S_d(1) = S(0)d_0 + \theta\left(\alpha\dot{S}(1) - S(0)\right) \tag{12}$$

Both parts of Equation 12 represent the risk-neutral binomial expression of Equation 10 in consideration of our assumptions and modifications. Figure III.1-6 depicts an exemplified binomial tree model for three future periods. In a generalized form, we introduce $S_{Z_{t-1}}(t)$ for $t > 0$ as the general expression for arbitrary nodes in the tree. In an according recursion formula, Z_{t-1} indicates the composition ("history") of all time-dependent factors for up and down movements $z_n \in \{u_n, d_n\}$, which the algorithm has calculated over all passed time steps $n = \{0, \dots, t-1\}$ up to that period t (e.g., $Z_2 = \{z_0, z_1, z_2\}$ in $t = 3$). As we explain above, we need to avoid negative prices in the binomial tree model and, therefore, set the lowest possible price to zero:

$$S_{Z_{t-1}}(t) = \max\left\{S_{Z_{t-2}}(t-1) * z_{t-1} + \theta\left(\alpha\dot{S}(t) - S_{Z_{t-2}}(t-1)\right);\ 0\right\} \tag{13}$$

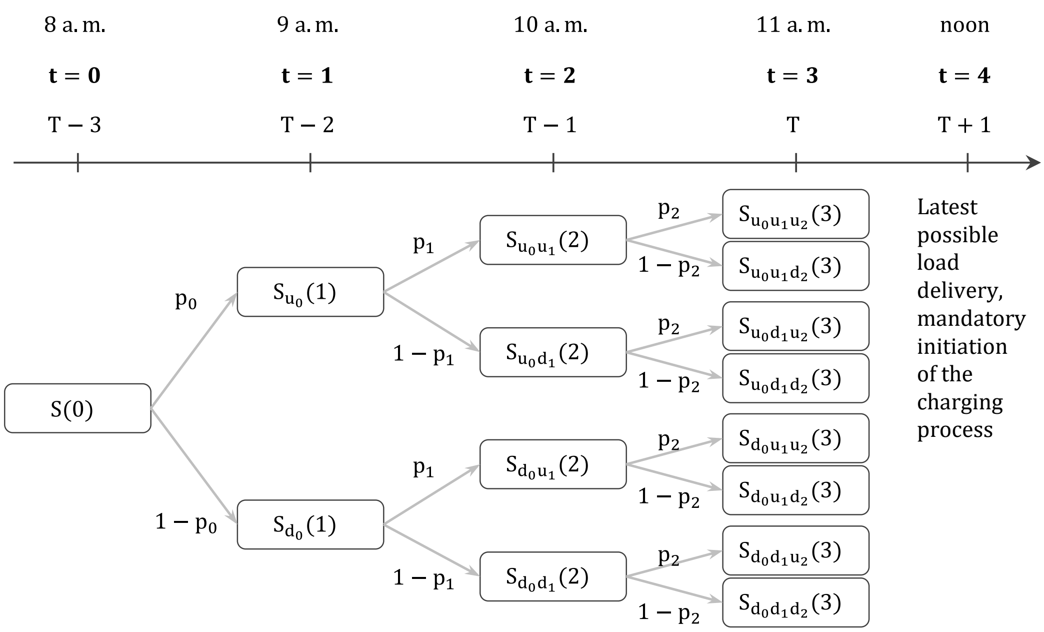

Figure III.1-6: Binomial tree model for an exemplified scenario

For example, if we wish to model the spot price in $t = 2$ after two up-movements, we obtain: $S_{Z_0}(1) = \max\{S(0) * u_0 + \theta(\alpha\dot{S}(1) - S(0)); 0\}$ with $Z_0 = \{u_0\}$ (first period) and $S_{Z_1}(2) = \max\{S_{Z_0}(1) * u_1 + \theta(\alpha\dot{S}(2) - S_{Z_0}(1)); 0\}$ with $Z_1 = \{u_0, u_1\}$ (second period). Note that $S(0)$ is the price which is (in this example) currently observable on the electricity spot market.

This modified GBM is a chain of single-period stochastic processes according to Equation 10, each calibrated in every time step. It conveys a plausible depiction of the spot price development of single-hour electricity contracts, with time-dependent historical mean prices and volatilities of the hour-to-hour returns reflecting intraday patterns. We consider IS implementation in the LS context to be able to cope with the high complexity (2^{t}) involved in the binomial tree. Heuristics may help to obtain analytical results for longer periods under consideration if necessary.

To appraise the binomial tree's applicability, we apply it to a simple real-world scenario. Our example depicts the charging process of a plug-in electric vehicle (PEV). The commuting user of the PEV reaches the workplace at 8 a.m. $(\mathrm{t}=0)$ on a winter day and connects it to a power outlet. The user gives the utility the right to defer the charging process throughout the morning provided the vehicle is ready for reuse at 1 p.m. For this example, we assume that the car can fully charge in one hour due to the charging outlet's charging speed or the car battery's remaining capacity. Hence, the utility can procure the necessary electricity as one single-hour contract but must initiate the process no later than noon. The utility hourly decides to either initiate the charging or defer the load by another hour. It may use its LS right at 8 a.m., 9 a.m., 10 a.m., and 11 a.m. In case the utility has not released the load by 11 a.m. $(\mathrm{t}=3)$, the LS window closes: at noon, the utility must initiate the charging process because the deferral option has expired at 11 a.m.

III.1.4.3.4. Value Determination

Although the concept of real options is distinct from financial options in the type of the underlying, ROA reverts to financial options in one respect: one can valuate a real option by replicating it as a financial option (Copeland & Antikarov, 2003). We can model the designed deferral option as a call option. A call option is a right, but not an obligation, to buy an object (e.g. an asset) at a previously fixed price. This technical model is interpretable in the short-term LS context: to serve a load, a utility must procure electricity from the real-time market. The timing of this investment is variable; through LS, the utility gains the right to defer the purchase of the necessary electricity contracts. Up to the option's expiration in time T, while the right to defer is valid, the utility can decide to buy the next available electricity contract on the spot market and emit the initiating control signal for load delivery through AMI. Exercising the option during that time span means expecting a monetary advantage compared to initiating the load at the latest possible time. The latter is the period after expiration $(\mathrm{T}+1)$:

if the utility has not served the load by expiration T, in the following period, it will be obliged to do so because the right to defer has expired.

We set the exercise or strike price K equal to the adjusted long-term mean at one hour after the deferral option's expiration so that exercising the option (i.e., serving the load) any earlier will precipitate an expected monetary advantage:

$$\mathrm{K} = \alpha\dot{\mathrm{S}}(\mathrm{T}+1) \tag{14}$$

We compute α as the ratio between the sum of realized spot prices at the recent n hours before the initial period ($t = 0$), and the sum of corresponding long-term means:

$$\alpha = \frac{\sum_{x=1}^{n} S(0-x)}{\sum_{x=1}^{n} \dot{S}(0-x)} \tag{15}$$

Note that, since we use ROA, α has to be constant for each process simulation because common option pricing models presume a constant strike price K.

Specifically, one models a deferral option as an American call. This type of a call option features the characteristic of being exercisable at any period during its lifetime. Therefore, a DSS using this model would need to execute three steps iteratively to optimally procure electricity from the market:

1) Model the electricity spot price pursuant to Section III.1.4.4.3
2) Calculate option values for every node in the binomial tree by going through it systematically in reverse, from end nodes to root (i.e., to the point in time at which one has to make the decision), and
3) Decide whether exercising the option is preferable at the current hour. If not, the system would wait for the next hour's spot price to become observable, then update the information and start again at step 1.

This procedure iterates until the option expires.

Regarding step 2, one needs to assign option values to every node in the tree to make the decision between exercising the option at the current point in time and waiting until the next hour. Considering the leaves of the tree (also known as end nodes) at expiration T, either: 1) the expected spot price in T is higher than strike price K, which means the mandatory delivery in $T + 1$ would be preferable and would render the option worthless; or 2) the expected spot price in T is below (or equal to) the strike price, which indicates one would prefer exercising the option. Again, one can use the composition of all states Z_{T-1} to refer to individual nodes. Depending on Z_{T-1}, the option values $C_{Z_{T-1}}(T)$ for the leaves of the binomial tree equal the differences between the strike price and the respective current spot prices (i.e., the expected monetary advantage) unless the option is worthless:

$$C_{Z_{T-1}}(T) = \max\left\{K - S_{Z_{T-1}}(T);\ 0\right\} \tag{16}$$

Proceeding from T to $T-1$ $[T-m]$, another possibility exists. Since the option has not expired yet, it may be preferable not to exercise said option but to wait until period T $[T-m+1]$. Since we have already calculated the option values for this following period, we can constitute an expected value using the probability for an upside or downside scenario from Equation 11.

With the two aforementioned possibilities, one determines the option value in each node as the maximum of either the value of exercising the option or the value of deferring the decision until the next hour. This procedure yields the following general formula for an m-th recursion, with $m \in \{1, \dots, T\}$:

$$C_{Z_{T-m-1}}(T-m) = \max\left\{\begin{matrix} K - S_{Z_{T-m-1}}(T-m); \\ p_{T-m} * C_{Z_{T-m-1},u_{T-m}} + (1-p_{T-m}) * C_{Z_{T-m-1},d_{T-m}} \end{matrix}\right\} \tag{17}$$

Generally, for each node in the binomial tree, we can determine the theoretical value of exercising (i.e., serving the load) at particular times and compositions of states. After having computed all option values from $t = T$ down to $t = 0$, the DSS can finally suggest whether exercising the option to procure electricity from the market at the current point in time is preferable—in other words, worth more than waiting considering the expected value of the whole binomial tree. If exercising the option at the current point in time is not preferable, the system would wait for the next hour's spot price to become observable and calculate an updated binomial tree to decide on exercising the option again. This procedure iterates until the algorithm exerts the option or the option expires. We can finally derive the value of LS by comparing the spot price at the starting point of the option (at which point the utility would have served the load without using the consumer's flexibility) to the realized purchasing price that the DSS chooses.

On a remaining note, Ullrich (2013) identifies necessary assumptions for validly applying financial option pricing models for ROA. The author surveys existing publications and concludes that many authors applying option pricing models neglect requirements. We verified our ROA method for real-time markets as being a valid application of financial option pricing models because it meets several important requirements. Following Ullrich (2013), we first confirm that our real-time model fulfills the assumption of a “complete market” because the electricity markets enable continuous trade of our model’s underlying object (physical electricity contracts). Second, the spot prices for physical electricity contracts evolve according to several tied and discretized (single-period) GBMs with corresponding constant variances. Third, the strike price is visible to the algorithm and constant throughout the option’s duration. Fourth, the maturity of the option is also visible and specified because it derives from the length of the LS window, with defined times of possible exercise.

III.1.4.4 Contracts Unavailable for Hour-ahead Procurement

The availability of electricity contracts in hour-ahead markets is limited. For a given day, the 24 single-hour contracts only become available following the day-ahead auction (e.g., 3 p.m. on the previous day at EPEX SPOT). Therefore, the LS window might span more hours than electricity contracts are available for procuring on the hour-ahead market, which is typically the case if a consumer grants LS flexibility beyond midnight before the following day’s contracts become available.

Consider an example of a utility that needs to make an initial LS decision at 1 p.m., which is before the hour-ahead markets of EPEX SPOT and Nord Pool Spot open for the following day. A consumer grants flexibility to defer a load until the next morning. At 1 p.m., it is not possible for the utility to take electricity contract spot prices for delivery hours after midnight into consideration. Such spot prices for early morning hours are, however, often lower than for delivery hours during the day or evening (see Section III.1.4.4.1).

If the utility would limit itself to procuring electricity contracts available at 1 p.m., the utility could only schedule load delivery before midnight and would therefore cede the savings potential of later delivery hours. Instead, it should employ the valuation method for procuring contracts from the real-time market to assess the value of LS beyond midnight. The spot price for the last contract available in hour-ahead trade becomes $S(0)$ in the model. The utility then calculates and compares the LS value based on real-time procurement to the riskless alternatives in the hour-ahead market. It decides for the more rewarding option. If LS beyond midnight appears more rewarding, the utility revisits this decision hourly, particularly once the spot prices for the following day’s electricity contracts become observable in the hour-ahead market. We refrain from presenting the case in more detail since it combines the static hour-ahead and dynamic real-time procurement cases.

III.1.5 Evaluation

III.1.5.1 Evaluation Approach

DSR methodology calls for evaluating a developed artifact to provide evidence that the artifact is useful (Gregor & Hevner, 2013). To assess its usefulness, we again distinguished between our models for hour-ahead and real-time procurement. The first model (see Section III.1.4.3), which deals with procuring electricity from the hour-ahead market, involves a simple choice between available electricity contracts. No disadvantages can result from following this logic, so we did not additionally evaluate the model. For the second model (see Section III.1.4.4), which deals with procuring electricity from the real-time market, the developed dynamic valuation method incorporates a stochastic price model and a binomial tree model. Following Hevner et al. (2004 , p. 86), “the selection of evaluation methods must be matched appropriately with the designed artifact and the selected evaluation metrics”. Possible evaluation methods for DSR include a case study, optimization, simulation, or informed argument. We took an ex post perspective and compared the prices a utility pays to procure electricity for an arbitrary load delivery with and without LS flexibility. A negative difference can result. The virtual savings our model achieved in many different simulated scenarios indicate the method’s effectiveness.

Based on historical data from EPEX SPOT, we tested a set of random LS scenarios that could have occurred in the past. We randomly drew a date and time at which a consumer could have granted LS flexibility. Then we took the historical spot price at the initiating date and time as the starting point to the operations in our model. Historical statistics provided spot price means and return volatilities appropriate for the season and the hour of the day. On this basis, we used our modified GBM to forecast spot price development. A second draw generated the length of the LS window. With values between 1 and 12 hours from the initiating time, we considered the deferral of delivery long enough to realistically cover most LS scenarios yet short enough to avoid distorting simulation results with overly optimistic or unrealistic scenarios. Up to the latest possible delivery hour, a historical spot price series provided the necessary benchmark for decisions.

Following our method, we then generated a binomial tree and employed our recursive formulae to derive the value of the deferral option—at first, for the initiating period. In each period, the algorithm repeatedly decided on initiating or postponing load delivery. Reiterating until the model indicated that delivery was preferable, the algorithm derived the time of load delivery. By comparing the historical spot price at this chosen hour to the initial spot price, we calculated the saving (positive or negative) that would have been realized in the simulated scenario by adhering to our method. Running through LS scenarios that could have occurred over three recent years (1 June 2011 to 31 May 2014), we repeated this approach 500,000 times. Although 10,000 simulation runs already showed similar overall results, a larger number increased the results' quality for sensitivity analyses.

Parameter		**Value**
Simulation runs		500,000
Evaluation data count		18,794
Historical reference timespan [a]		Randomized
Date and time of LS initiation	t_0	Randomized
Expiration, or LS window length [h]	T	Randomized
Mean-reversion speed	θ	Randomized
Adjustment reference interval [h]		Randomized
Adjustment factor	α	Computed
Risk-free interest rate	r_f	0
Time increment [h]	Δt	1

Table III.1-2: Evaluation parameters

To automate this simulation, we implemented the created artifact prototypically in the form of an Excel workbook supported by Visual Basic for Applications (VBA) macros. Table III.1-2 depicts the evaluation parameters we employed. Among these parameters, we randomized the historical reference timespan (10, 5, 3, or 1 years) for seasonal statistics, the mean-reversion speed θ (between 0 and 1, inclusive) and the reference interval for computing the adjustment factor α (1 to 48 recent hours or no adjustment at all), to compare those parameter values as the basis for LS decisions.

III.1.5.2 Results and Discussion

Summarizing all scenario results of our ex post simulation, we determined the average (AV) savings a utility would have realized by seizing LS flexibility and the corresponding standard deviations (SD) that depict volatility. Figure III.1-7 illustrates the distribution of absolute savings in a histogram. The interval of 0–2 €/MWh that depicts small savings featured the most observations. However, we saw a high frequency of scenarios (12.8 percent) with savings ≥ 20 €/MWh. LS based on our prediction also sometimes turned out negative when spot prices developed in a direction other than predicted. Yet, one can see that our approach provided a benefit in the majority of scenarios (72.3 percent). We also computed relative savings, which express the realized absolute savings at load delivery as a fraction of the respective spot prices at LS initiation ($\frac{S_0 - S_t}{S_0}$). On average, LS according to our designed method yielded positive results in a relevant magnitude. It achieved average savings of 4.93 €/MWh (or 11 percent) over all randomized input parameters. The standard deviation amounted to 17.51 €/MWh or 39 percent of the initial spot price S_0, which, in turn, averaged to 44.45 €/MWh (or 100 percent).

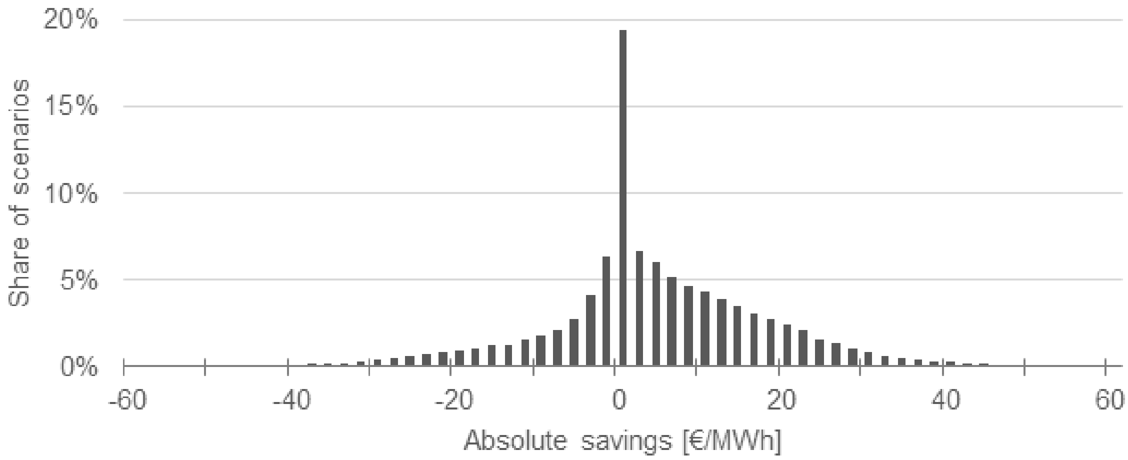

Figure III.1-7: Histogram of absolute savings (in intervals of 2€/MWh)

To discuss our evaluation results, we distinguish between sensitivity in the scenarios and in the model parameters. Table III.1-3 contains results regarding scenario sensitivity.

We observed the lowest relative savings in summer scenarios. This result might be related to low volatility in electricity prices in the summer (12.32 €/MWh, c.f. Table III.1-1) since less differences in spot prices over a LS window mean less savings potential. However, a counterargument is the observation that volatility in intermediate seasons was similarly low (15.39 €/MWh), while intermediate season scenarios featured the highest average savings.

We further observed that realizable savings rose as the length of the LS window increased. Accordingly, we conducted a Wilcoxon signed-rank test for matched pairs. This statistical test indicated to maintain the null hypothesis of the averaged relative savings being dependent on the according deferral option maturities. We additionally measured a Pearson product-moment correlation coefficient of 0.9953 between the LS window length and averaged relative savings. Hence, the monetary value of LS flexibility increases for every additional period in the LS window.

	AV absolute savings [€]	**SD absolute savings [€]**	**AV relative savings [%]**	**SD relative savings [pp]**	**Scale (rel. savings)**
Overall	**4.93**	**17.51**	**11.1**	**39.4**	**1.00**
Season					
Summer	4.32	12.42	9.5	27.4	0.86
Intermediate	5.43	15.57	12.2	35.1	1.10
Winter	4.54	24.22	10.4	55.4	0.94
LS window length [h]					
1	1.74	17.01	3.9	38.2	0.35
2	2.68	17.14	6.0	38.4	0.54
3	3.30	17.59	7.4	39.5	0.67
4	3.82	17.13	8.6	38.6	0.77
5	4.44	17.44	10.0	39.1	0.90
6	4.92	17.32	11.1	39.0	1.00
7	5.30	17.53	12.0	39.6	1.08
8	5.87	17.73	13.2	39.9	1.19
9	6.25	17.92	14.1	40.4	1.27
10	6.62	17.74	14.9	40.0	1.35
11	7.25	17.88	16.3	40.2	1.47
12	7.65	17.76	17.3	40.1	1.56

Table III.1-3: Ex post simulation results (scenario sensitivity)

To study the sensitivity of savings to our model parameters, we analyzed simulation results in dependence of changes in parameter values. Table III.1-4 depicts a selection of the tested parameters.

First, we generated scenarios with four historical reference timespans for seasonal statistics and intraday patterns. We discuss our observations even though no statistical comparison was valid due to the small, discrete sample. We saw no substantial difference between the three more recent timespans (1, 3, and 5 years) in average relative savings. A reference timespan of 10 years seemed to result in lower savings. This finding suggests that the more recent timespans describe similar situations in the EPEX SPOT market and, therefore, better suit basing LS decisions on. In contrast, 10 years may be too long a timespan to account for developments such as the fast growing integration of renewable energy sources.

Second, we checked whether adjusting the seasonal spot price levels to short-term effects by using the adjustment factor α increased savings. A statistical t-test of a sample of average relative savings under short-term adjustment (48 reference intervals forming $\alpha \neq 1$) against the relative savings without adjustment ($\alpha = 1$) indicated to reject the null hypothesis of the means being equal ($p = 0.000$***). As such, we can infer that the adjustment factor α is a relevant component to our model. With short-term adjustment present, results were superior compared to no adjustment, even though one cannot judge how many hours should optimally serve as the reference interval to this adjustment. Short-term effects, such as the amount of current electricity demand and production, events (e.g., soccer world cup finals), holidays, or weather, seem to influence spot prices, and adjusting the model expectations seems prudent.

Third, we checked if introducing mean reversion toward the long-term mean increased savings. Indeed, a statistical t-test of a sample of average relative savings under mean reversion (100 mean-reversion speeds $0 < \theta < 1$) against relative savings without mean reversion ($\theta = 0$) indicated to reject the null hypothesis of the means being equal ($p = 0.000$***). As such, we can infer that mean reversion is a relevant component to our model. Spot price prognosis benefits from considering intraday patterns and, thus, contributes to our model's decision value. However, one cannot determine an optimum for the mean-reversion speed parameter $0 < \theta < 1$ with sufficient significance.

	AV absolute savings [€]	**SD absolute savings [€]**	**AV relative savings [%]**	**SD relative savings [pp]**	**Scale (rel. savings)**
Overall	**4.93**	**17.51**	**11.1**	**39.4**	**1.00**
Historical ref. timespan [a]					
1	**5.25**	**17.49**	**11.8**	**39.3**	**1.06**

	AV absolute savings [€]	SD absolute savings [€]	AV relative savings [%]	SD relative savings [pp]	Scale (rel. savings)
3	5.21	17.62	11.7	39.6	1.06
5	5.11	17.47	11.5	39.3	1.04
10	4.15	17.46	9.3	39.3	0.84
Mean-reversion speed θ					
0.00	3.13	17.30	7.0	39.0	0.64
0.05	3.81	17.52	8.6	39.4	0.77
0.10	4.29	17.22	9.7	38.8	0.87
0.15	4.51	17.98	10.2	40.6	0.92
0.20	4.45	17.10	10.0	38.5	0.90
0.25	4.43	17.58	10.1	40.0	0.91
0.30	4.81	18.51	10.8	41.8	0.98
0.35	4.86	17.74	10.9	39.8	0.98
0.40	4.78	17.59	10.8	39.6	0.97
0.45	5.06	17.47	11.4	39.3	1.03
0.50	4.76	17.31	10.7	39.0	0.97
0.55	4.97	16.99	11.1	38.0	1.00
0.60	5.07	17.41	11.4	39.0	1.02
0.65	5.10	17.50	11.5	39.3	1.03
0.70	5.08	17.03	11.4	38.3	1.03
0.75	**5.32**	**17.10**	**11.9**	**38.3**	**1.08**
0.80	5.22	16.66	11.7	37.2	1.05
0.85	5.18	17.29	11.7	38.9	1.05
0.90	5.11	17.88	11.5	40.3	1.04
0.95	5.26	16.82	11.8	37.8	1.07
1.00	5.31	17.42	11.9	39.0	1.07
Adjustment ref. interval [h]					
No adjustment	4.01	17.56	9.0	39.6	0.82
1	5.18	17.62	11.6	39.5	1.05
2	5.07	16.83	11.4	37.8	1.03
3	5.13	17.15	11.5	38.6	1.04
4	4.90	17.32	11.0	38.9	0.99

	AV absolute savings [€]	SD absolute savings [€]	AV relative savings [%]	SD relative savings [pp]	Scale (rel. savings)
5	4.93	17.07	11.1	38.6	1.01
6	4.96	17.16	11.2	38.6	1.01
7	5.25	18.00	11.7	40.2	1.06
8	**5.62**	**17.50**	**12.6**	**39.1**	**1.13**
9	4.89	17.38	11.1	39.2	1.00
12	5.09	17.44	11.4	39.1	1.03
18	4.85	18.51	10.9	41.8	0.99
24	5.08	17.36	11.4	38.9	1.03
30	5.01	17.91	11.3	40.4	1.02
36	5.02	18.81	11.3	42.5	1.02
42	4.89	17.07	10.9	38.2	0.99
48	4.90	17.39	11.0	39.2	1.00

Table III.1-4: Selected ex post simulation results (model sensitivity)

We observe that our decision support model resulted in average savings of positive, relevant magnitude. To study the impact of model training on the savings potential, we selected one exemplary set of input parameters: a historical reference timespan for seasonal statistics of one year, the mean-reversion speed $\theta = 0.75$, and a reference interval for short-term adjustment of eight hours. As Table III.1-4 shows, scenarios with each of these input parameters resulted (ceteris paribus) in the highest savings in an EPEX SPOT setting. We are aware that this combination will not automatically cause the highest savings overall. Yet, to provide a conservative indicator for our model's usefulness, the trained parameter set resulted in average savings of 5.80 €/MWh (or 12.9 percent) as Table III.1-5 shows. It also featured a 16 percent lower volatility. We note that, to achieve highest savings overall, one would have to analyze all combinations of model parameters by, for example, an ex post simulation similar to the one we conducted. In addition, when employing the model on another electricity market, one would also need to independently analyze the parameters.

	AV absolute savings [€]	SD absolute savings [€]		AV relative savings [%]	SD relative savings [pp]	Scale (rel. savings)
Reference	4.93	17.51		11.1	39.4	1.00
	Trained parameter set					
Overall	**5.80**	**14.86**		**12.9**	**33.1**	**1.17**

	AV absolute savings [€]	SD absolute savings [€]		AV relative savings [%]	SD relative savings [pp]	Scale (rel. savings)
12 hour LS window	8.52	17.16		19.2	38.8	1.73

Table III.1-5: Selected ex post simulation results (trained parameter set)

Even though application scenarios and model assumptions differ, the savings that our models yields stand the comparison to other relevant DR literature. Feuerriegel and Neumann (2014) build a LS scenario for utilities that can procure futures derivatives and participate in day-ahead auctions. In their optimization scenario, they calculate that fully exploiting LS over windows of up to 24 hours would yield averaged absolute savings of 12.30 €/MWh. They further note that savings increase as LS windows get longer. If we assume an equal average LS window length of 12 hours and use the trained parameter set, we can compare our method. As Table III.1-5 indicates, it would yield averaged absolute savings of 8.52 €/MWh. However, Feuerriegel and Neumann (2014) allow for shifting loads to a time earlier than the scheduled time, which enables higher flexibility and savings but is not possible in a real-time scenario. This difference weakens comparability, which one needs to respect when judging the lower amount our model potentially saves on real-time markets. Sezgen et al. (2007) calculate the option value of LS with the help of thermal energy storage systems, which enable LS also in day-ahead markets. In their average case for storage efficiency, the option to shift loads reaches a value of approximately 199,000 $/MW over five years of operation (20 days a month), which equals 6.91 $/MWh or 6.17 €/MWh (average exchange rate in June 2015). Our results are of similar magnitude, although Sezgen et al. (2007) designed their approach for day-ahead markets with according market differences. Fridgen, Mette, and Thimmel (2014) simulate the potential of LS in a real-time scenario in which electric vehicle drivers can use AMI to provide information about the start of their next trip to utilities that seek to flexibly deliver loads. In the given scenario, utilities' savings on charging batteries average between 3.1 and 7.3 percent, which they can use to compensate customers. Our method can potentially save more. Finally, in a hypothetical ex post assessment, we computed that perfect information (in other words, price certainty) could have yielded a maximum of 21.5 percent relative savings. Given that our method saved 11.1 percent, we conclude that it worked quite well.

Altogether, we find the following generalizable insights. First, we conclude that one can use ROA to quantify the value of IS-enabled flexibility in electricity consumption. Second, the option to shift loads bears a positive value. Third, we deem our valuation method advantageous to current practice. We successfully conducted an additional proof-of-concept of our evaluation with real-time prices from the U.S. and found similar results. As such, we see no reason to expect that our model does not apply to markets other than EPEX SPOT.

III.1.6 Conclusion

The transition to renewable energy sources entails DR efforts to balance increasingly volatile supply through shifting demand. In this paper, we establish a method to valuate the flexibility of deferring electricity consumption at the time an individual consumer grants such flexibility. Utilities can use the ability to quantify the monetary value of LS when they decide on compensations for the consumer who approves LS. We present three cases that differ mainly in whether they involve an hour-ahead market. If a utility has the option to procure electricity contracts in advance, it can lock in a monetary advantage by purchasing the cheapest contract(s) out of the ones available for upcoming delivery hours of the day, as long as they fall in the flexibility period that the consumer allots. Utilities can procure contracts ex ante in the short term on the hour-ahead markets of European electricity exchanges. In electricity exchanges with no hour-ahead market, utilities need to decide whether to deliver the load immediately or at a later point in time basing on predictions. One should be able to apply our generic real-time model to various electricity markets around the world, such as spot markets in the United States and Europe. We establish an appropriate artifact based on the theoretical foundation of real options theory. Addressing a prerequisite, we also develop a stochastic process replicating real-time spot price development in a simple and realistic manner.

Our formal modeling approach has some rather technical limitations. First, the stochastic process for our dynamic real-time market model cannot consider negative spot prices, which can arise in situations of excess supply. Second, we use a standard Wiener process to describe uncertainty, which implies a normal distribution. However, electricity prices feature rather heavy-tailed distributions. Third, anomalies such as technical breakdowns or faulty scheduling in electricity supply can cause immediate and unpredictable price movements (“spikes”) that our stochastic process cannot predict. For all three reasons, the modified GBM simplifies reality, but it proves useful by enabling ROA.

The value derived in our real-time model is typically set on a lower bound for three reasons: first, LS can substitute balancing power in some cases—a significant saving that exceeds the value calculated in our model. Second, preventing peak workload in distribution grids decreases necessary investments in expanding the power grid and in conventionally producing power. Thirdly, in a cautionary approach, we excluded negative electricity spot prices, which have occurred rarely so far but may occur more frequently in the future. To date, our hour-ahead market model is a static approach that does not consider changing external conditions while a utility shifts load. In future research, multiple simultaneously modeled real options for every hour of the intraday market could enhance the savings potential for utilities. Moreover, future research can help develop incentive-compatible tariff structures based on compensations that utilities can offer consumers. Scholars can design application systems for utilities that integrate our valuation model in algorithms. Although we identify ROA as an appropriate approach to identify the value of consumption flexibility, future research could compare the results with another methodology, such as dynamic stochastic optimization.

With our real options approach, we help assess the economic potential of IS-enabled, short-term flexibility in electricity consumption. Our results confirm that real options theory suits evaluating flexibility in IS research and energy informatics in particular. We see similarly promising applications in studying on-demand usage of, for example, cloud computing services and dynamic capacity allocation in business process management. As such, we provide a viable basis to further research consumption flexibility in IS domains and to valuate such flexibility in business practice.

III.1.7 References

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III.2 Research Paper 5: "Decision Support in Building Automation - A Data-driven Demand Response Approach for Air Conditioning Systems"

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Working Paper	

Abstract:

Building operation faces great challenges in electricity cost control as prices on electricity markets become increasingly volatile. Simultaneously, building operators could nowadays be empowered with information and communication technology that dynamically integrates relevant information sources, predicts future electricity prices and demand, and uses smart control to enable electricity cost savings. In particular, data-driven decision support systems would allow the utilization of temporal flexibilities in electricity consumption by shifting load to times of lower electricity prices. To contribute to this development, we propose a simple, general, and forward looking demand response (DR) approach that can be part of future data-driven decision support systems in the domain of building electricity management. For the special use case of building air conditioning systems, our DR approach decides in periodic increments whether to exercise air conditioning in regard of future electricity prices and demand. The decision is made based on an ex-ante estimation by comparing the total expected electricity costs for all possible activation periods. For the prediction of future electricity prices, we draw on existing work and refine a prediction method for our purpose. To determine future electricity demand, we analyze historical data and derive data-driven dependencies. We embed the DR approach into a four-step framework and demonstrate its validity, utility and

quality within an evaluation by using real-world data from two public buildings in the US. Thereby, we address a real-world business case and find significant cost savings potential when using our DR approach.

III.2.1 Introduction

To date, energy transition is mostly pushed forward in advanced European economies (e.g., Germany, Norway, Sweden, Switzerland), but there is also a world-wide political endeavor (e.g., South America, Japan) to stop global warming (World Economic Forum 2017). With an increasing number of countries aiming for an entirely sustainable energy production (especially from wind and solar), sustainable energy sources evolved to be the world's (relatively) fastest-growing energy source (U.S. Energy Information Administration 2018). The adverse effect of sustainable energy sources is their lack of controllability (e.g., sun shining, wind blowing), which brings volatility to energy supply (Goebel 2013; Ludig, et al. 2011). As a result, the expansion of sustainable energy sources results in more volatile electricity prices (Smith, et al. 2010; Ketterer 2014).

Additionally, the world's energy consumption is projected to increase by 28% between 2015 and 2040, especially due to increased economic growth, access to marketed energy, and quickly growing populations in non-OECD countries (U.S. Energy Information Administration 2017) that outweigh increasingly energy efficient technologies. Thereby, in 2017, domestic and commercial building sectors' combined contribution to U.S. energy consumption has reached 27% (U.S. Energy Information Administration 2018) and is projected to increase by 32% between 2015 and 2040, an increasing proportion of which is electricity consumption with an annual increase of 2% (U.S. Energy Information Administration 2017). Thus, for building operation, which has the objective to manage buildings and their facilities (e.g., technical infrastructure, heating, ventilation and air conditioning), volatile electricity prices are a difficult challenge and electricity demand management is an important task.

Building operators can reduce their volatility-exacerbated electricity costs by utilizing flexibility in electricity consumption, which "bear[s] economic value" (Fridgen, et al. 2016: p.538). As electricity prices – depending on the market – are likely to be lower during some periods (e.g., night times), it is preferable to consume electricity in these periods rather than during periods, in which prices are regularly at their peak (e.g., noon). Following Rozali, et al. (2014: p.2464), load shifting (LS) defines the “process of reallocating the electricity demands from the peak periods when the electricity tariff is high, to off-peak periods when the electricity tariff is low”. While LS is usually not possible for the entire electricity demand, already minor LS flexibilities can yield substantial electricity cost savings. More precisely, certain appliances are interactive and usually lack flexibility potential (e.g., television, lighting, stove, office equipment) (Barker, et al. 2012), however, other appliances may contain flexibility potential that can be utilized by smarter control systems (e.g., air conditioning systems, water boiler, washing machine). The research domain for utilizing LS flexibility is called demand response (DR). DR is defined as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time […]” (Federal Energy Regulatory Commission 2008: C-2).

In U.S. building operation, a/c systems are an important influencing factor of electricity costs (U.S. Energy Information Administration 2016) and denote a sub-category of building automation systems, i.e., systems which are “widely employed in modern buildings to realize automatic monitoring and control of building services systems” (Liu, et al. 2009: p.1138). Nevertheless, to this day, there are many a/c systems that are manually controlled (Ferreira, et al. 2012) and prone to run constantly throughout the day, even during disused hours on working days, weekends, and night times. These a/c systems possess LS flexibility potential by reducing a/c to the on-demand usage in advance to the occupancy of a room or building. Other a/c systems provide “automatic control of the indoor environment conditions” (Ducreux, et al. 2012: p.4847) and either preset a/c activation to a fixed time of day or trigger a/c activation by temperature measurements within the building’s sensor networks.

Opposite to these approaches, the present paper aims to contribute to the development of data-driven decision support systems (DSS) that make a/c additionally cost-sensitive. In general, DSSs are “computer technology solutions that can be used to support complex decision making and problem-solving” (Shim, et al. 2002: p.111). According to the “Expanded DSS Framework” of (Power 2008: p.127), the special type of data-driven DSS “emphasizes access to and manipulation of a time series of internal […] data and sometimes external and real-time data”. Data-driven DSSs can significantly improve electricity management for a/c systems by monitoring and processing decision-relevant information from different information sources. They can integrate both building-specific information (e.g., current and required inside temperature, occupancy schedules) and external information (e.g., historical and real-time electricity price information, weather information) to enable ex-ante optimal LS decision making. Compared to many existing approaches on building automation, these decisions are time-saving and cost-saving under consideration of human objectives and frame conditions. Hence, the present paper covers a relevant real-world problem:

> *"How can data-driven decision support for load shifting reduce electricity costs in real estate air conditioning systems?"*

For the creation of data-driven DSSs, smart and machine supported information systems are of great value. An advanced metering infrastructure (AMI) as a subcategory of information and communication technology (ICT) records "customer consumption (and possibly other parameters) hourly or more frequently and provides for daily or more frequent transmittal of measurements over a [bidirectional] communication network to a central collection point" (Federal Energy Regulatory Commission 2008: p.5). Therefore, AMI enables rapid information exchange and remote control for activating and deactivating a/c systems.

A building operator's LS decision on a/c depicts a dynamic and stochastic optimization problem. Therefore, this paper presents an artifact to address this real world problem by following principles of the design science research (DSR) paradigm (Gregor and Hevner 2013; Hevner, et al. 2004; Peffers, et al. 2007). The artifact comprises a DR approach for data-driven DSSs, which enables building operators to perform real-time decision making on LS. The DR approach is embedded into a standardized four-step framework and decision making is realized by an algorithm that requires building operators to set few input parameters. Thereby, the DR approach automatically searches for the expected optimal activation time of the a/c system within a specified temporal flexibility window. Three artifact requirements are postulated: It must be easy to understand and use, without requiring engineering expertise or thermal modeling (i.e. simple). It must be applicable for a broad range of applications scenarios (i.e. general), and it must integrate electricity price and demand prediction (i.e., forward-looking).

The paper is structured as follows: This section discusses the purpose and scope of the artifact and its relevance for the target audience (building operators). Section III.2.2 specifies the problem context in detail and presents findings from prior research. Section III.2.3 presents the artifact referred to as DR approach. Section III.2.4 contains the artifact demonstration and a rigorous design evaluation that underpins the validity, utility, and quality of the artifact based on a real-world business case with historical data from two large public buildings. Section III.2.5 summarizes results and discusses limitations and possible future research.

III.2.2 Related Work

The development of an artifact, which enables building operators to reduce electricity costs using ICT-enabled decision support, is a contribution to energy informatics (EI). EI is concerned with “analyzing, designing, and implementing systems to increase the efficiency of energy demand and supply systems” (Watson, et al. 2010: p.24). An application domain of EI is demand side management (DSM), which comprises “approaches such as the general increase in energy efficiency and time-based electricity pricing for end-consumers” (Feuerriegel and Neumann 2014: p.359). Strbac (2008) provides an overview of DSM, explaining both benefits and challenges. The author lists DSM as a means to reduce long-term electricity reserve, to reduce preventive measures for power system security, to improve operation efficiency, and to manage network constraints at the distribution level (Strbac 2008). DR is a subclass of DSM (Sui, et al. 2011), which is an umbrella term (Feuerriegel and Neumann 2014). DR is more customer-centric by promoting their interaction and responses to market signals (e.g., electricity prices) (Albadi and El-Saadany 2008; Siano 2014; Palensky and Dietrich 2011). Fridgen, et al. (2016) propose a DR valuation method for LS flexibility from a utility’s perspective by using real option analysis. They build on prior research applying real option analysis (Benaroch and Kauffman 1999; Ronn 2002; Sezgen, et al. 2007; Ullrich 2013) and develop a model to dynamically optimize LS in discrete time increments. For households and small businesses, Conejo, et al. (2010) develop a model to dynamically adjust the hourly load level in response to consumption constraints and electricity prices, which are forecasted within confidence intervals. Lujano-Rojas, et al. (2012) present an optimal DR load management strategy, which considers electricity price prediction, user-defined preferences on energy demand, renewable power production, and electric vehicle utilization. In two case studies, they illustrate that users of the proposed model can reduce electricity bills between 8% and 22%. Presenting a tool to maximize social welfare, Su and Kirschen (2009) illustrate that electricity prices tend to decline by increasing usage of LS. In a case study, Albadi and El-Saadany (2008) demonstrate that DR reduces electricity price peaks and changes the consumption patterns of end-consumers. The authors list benefits of DR and find that savings are not only possible for participating customers, but for all customers in the market. Further, they find positive effects of DR on electricity system reliability and electricity market performance. Mohsenian-Rad, et al. (2010: p.329) use a game-theoretic approach to illustrate that in the presence of a real-time electricity market, each user has the incentive to participate in a scheduling game. They propose an "optimal, autonomous, and distributed incentive-based energy consumption scheduling algorithm" that aims to minimize "the cost of energy and also to balance the total residential load" (Mohsenian-Rad, et al. 2010: p.329). Further, they focus on communication among users rather than interactions between a utility company and its customers. For residential customers, Gottwalt, et al. (2011) build different scenarios with flat and time-based electricity tariffs. Without uncertainty in a day-ahead hourly pricing regime, households can realize significant savings in electricity costs.

In the context of commercial building operation, Zhou, et al. (2011) build an agent-based simulation model and illustrate that DR actions by several building operators shave load profiles at peak hours (peak clipping), reduce volatility of aggregated electricity demand, reduce electricity prices (and therefore electricity costs), and reduce electricity price volatility. Bahrami, et al. (2012) suggest a new load management strategy to reduce building operators' electricity costs. Their DR approach models electricity prices as a convex function of electricity demand and supply, i.e., an individual building operator's hourly market price is influenced by information about the total electricity consumption of all customers and the total generation capacity of the respective utility. However, since building operators usually lack such detailed market information, this approach is rather game theoretic and only applicable from a utility's perspective. A model for electricity price prediction is developed by Mohsenian-Rad and Leon-Garcia (2010) who propose an automatic energy consumption scheduling framework. Similar to the present paper's objectives, these authors intent to help building operators "to shape their response [to electricity prices] properly and in an automated fashion" (Mohsenian-Rad and Leon-Garcia 2010: p.121). While the present paper's approach takes into account the dependence of electricity demand on temperature forecasts, Mohsenian-Rad and Leon-Garcia (2010) require building operators to manually announce their upcoming electricity demand using AMI. Henze (2005) presents a model-based approach for predictive control of active and passive thermal storage inventory. Their supervisory controller includes short-term weather prediction and therefore a/c electricity demand prediction, time-of-use differentiated electricity prices, and real-time control strategies with dynamically updated forecasts. However, since these authors assume electricity rate structures to be visible and exogenously predetermined by the utility, their model is not suited for situations in which a building operator must decide based on real-time electricity market price information with stochastic future development. The present paper grasps this situation by applying a prediction methodology for intraday electricity price development under consideration of historical price patterns. Another approach that integrates dynamic electricity tariffs and electricity storage management is presented by Oldewurtel et al. (2011). Like the present paper's approach, these authors model dynamic electricity prices with stochastic future development to achieve electricity cost savings by exploiting LS flexibilities. Instead of predicting electricity demand, however, these authors empirically collect and aggregate historical demand profiles, which makes their model insensitive for individual electricity consumption.

Most of the mentioned studies rely on data-driven decision making and assume smart grids and respective ICT (especially AMI) as technological enablers. Concluding, researchers have already started to develop data-driven DR approaches by suggesting new control logics in building operation, which might be part of future DSSs. The present paper strives to contribute to this development by addressing especially one identified research gap: To the best of the authors knowledge, formal DR approaches which dynamically predict electricity prices and electricity demand for a/c systems based on weather information and occupancy schedules and that perform automated and real-time decision support on LS with the objective to reduce electricity costs do not exist so far.

III.2.3 Artifact Description

In this section, the present paper continues to "create and evaluate [the appropriate] IT artifact intended to solve [the] identified problem" (Hevner, et al. 2004: p.77). In line with the EI framework introduced by Watson et al. (2010), the artifact supports building operators by using flow networks (AMI) and sensitized objects (a/c system) to smarter consume electricity. Hence, it addresses the problem of a "lack of information to enable and motivate economic and behaviorally driven solutions" (Watson, et al. 2010: p.24).

III.2.3.1 Scenario Introduction

The present paper defines an "a/c system" as technology that building operators use to change temperature (i.e., heating, or cooling) inside a room or building. Although many authors use the term heating, ventilation and air conditioning systems, this paper applies a/c systems as a general term, which can comprise all these use cases. The a/c system is part of a greater information system that "ties together the various elements to provide a complete solution" (Watson, et al. 2010: p.27). In the following, the artifact's application scenario is explained along with prerequisite assumptions and the four-step framework embedding the DR approach to reduce electricity costs.

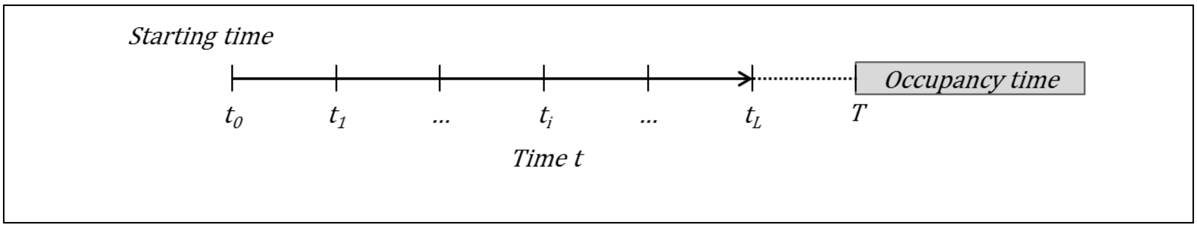


Figure III.2-1: Exemplary time scheme prior to occupancy time

The application scenario is characterized as follows: A building operator must prepare appropriate temperature according to an exogenously specified room or building (in the following referred to as object) occupancy schedule (Figure III.2-1). Occupancy time is the time, when the considered object is not empty. The required inside temperature ($\mathrm{temp}_{\mathrm{req}}$) needs to be achieved until occupancy starts (T) (and is assumed to be constant during occupancy), whereas inside temperature prior to occupancy may deviate. For the DR approach, the present paper focuses on the time span between the first possible starting time for a/c (t_0) and the latest possible starting time for a/c (t_L). The latter is necessary to guarantee $\mathrm{temp}_{\mathrm{req}}$ until occupancy: t_L is the latest point prior to T at which a/c activation ensures $\mathrm{temp}_{\mathrm{req}}$ until T. By finding the expected optimal point in time between t_0 and t_L (i.e., the temporal flexibility window for LS) to activate the a/c system, building operators can minimize expected electricity costs. During each day, several subsequent, non-overlapping events can take place in one object.

Assumption 1. *Building operators can deduce t_0 and t_L by analyzing the occupancy schedule and $temp_{req}$ is constant for different object occupancies.*

The DR approach uses the end of one occupancy as t_0 to optimize a/c for subsequent occupancy (if an occupancy is the first on the day, t_0 could be the previous day). Hence, due to previous occupancy, the object's inside temperature in t_0 can be assumed to equal $\mathrm{temp}_{\mathrm{req}}$. If a/c is deactivated in t_0, the object's inside temperature starts striving toward outside temperature due to thermal movement.

Assumption 2. *The object's inside temperature in t_0 equals $temp_{req}$.*

Considering the first artifact requirement ("easy to understand and use"), the DR approach applies discrete-time optimization, which is less complex and demanding (for decision makers and ICT) than continuous-time optimization. Moreover, the DR approach requires an appropriate a/c procedure, i.e., a sequence of a/c activations and deactivations with specific durations and intensities. A/c procedures are specified by their control levers: Cooling and heating can be activated unilaterally or alternately. Then, cooling and heating can be activated continuously or with interruptions. Finally, cooling and heating can be performed at different intensities within certain technical boundaries. These control levers can be applied either solely or jointly within one procedure. The common objective of all procedures is to achieve $\mathrm{temp}_{\mathrm{req}}$ until T.

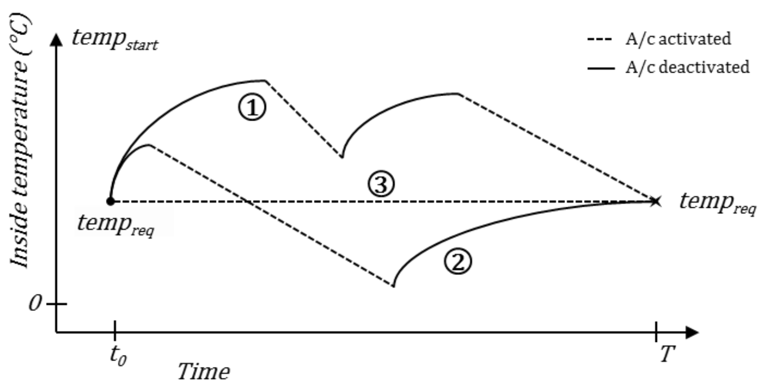


Figure III.2-2: Objective and variants of a/c procedures

Figure III.2-2 illustrates three exemplarily procedures (for cooling): A procedure where a/c is activated dynamically over multiple periods (1). At each discrete time step, an algorithm decides to either activate or deactivate a/c and, for activation, a/c intensity. Although the authors regard this to be a very promising procedure to minimize electricity costs for a/c, it also entails the largest optimization complexity. Then, a less complex procedure in which $\mathrm{temp}_{\mathrm{req}}$ (until T) is achieved by one-time activation and deactivation (2). To compensate for an object's thermal movement, inside temperature during activation (before T) is undercooled. However, this procedure has technical restrictions (e.g., the a/c system may cool below freezing point of cooling water) wherefore additional optimization conditions would be necessary. Finally, a procedure in which a/c runs constantly (without interruption) from t_0 to t_L (3). This procedure foregoes LS flexibility and is (in most cases) a waste of savings potential and energy.

The present paper applies a procedure that is more simplistic than procedure (1) and a combination of procedure (2) and (3) with modifications to avoid technical restrictions resulting from undercooling or overheating and to reduce the waste of energy: After activation, a/c is performed continuously and not allowed to interrupt. After reaching $\mathrm{temp_{req}}$, however, it is performed at lower intensity just to keep $\mathrm{temp_{req}}$ until T (Figure III.2-3).

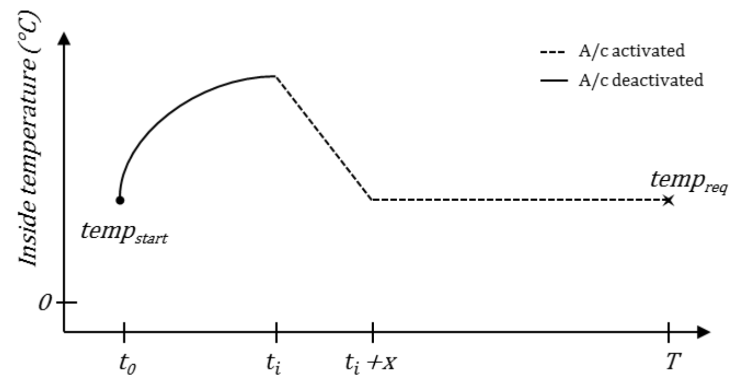


Figure III.2-3: The applied procedure

Thereby, $x \geq 1$ is the duration (number of discrete-time increments) after a/c activation until $\mathrm{temp_{req}}$ is restored. The algorithm of the DR approach starts in t_0 and examines whether immediate activation of a/c is expected to be optimal. The activation of a/c is expected to be optimal, if total expected electricity costs resulting from a/c activation in the current period until T are lower compared to later activation times. If a later activation is expected to be optimal, a/c is not activated and computation is repeated the next discrete time step (t_L at the latest).

III.2.3.2 Framework Introduction

The data-driven DR approach is embedded within a standardized four-step framework (Figure III.2-4). It consists of an inner cycle (decision algorithm for LS) and an outer cycle (feedback cycle). In step 1 (scheduling), the DR approach imports input information for data-driven decision making. In step 2, the DR approach predicts future electricity prices (a) and demand (b). This information is used in step 3, when the DR approach decides upon LS, i.e., activation of the a/c system. If activation is deferred, the DR approach reiterates step 2 and 3 in the next period. After optimization is completed, the DR approach evaluates realized cost savings (step 4). In the following, this paper explains each step and the accompanying assumptions in more detail.

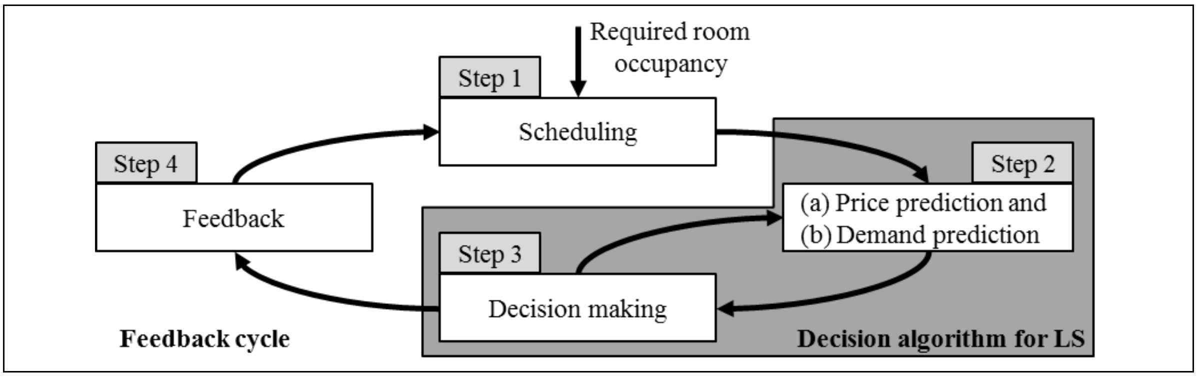


Figure III.2-4: Four-step framework of the DR approach

III.2.3.3 Step 1: Scheduling

The first step is the collection of three human input parameters according to Assumption 1: $\mathrm{t_0}$, $\mathrm{t_L}$, and $\mathrm{temp_{req}}$. $\mathrm{t_0}$ and $\mathrm{t_L}$ may be implicitly derived out of the object's occupancy schedule. These parameters strongly influence further decision making and set the boundaries for optimization.

III.2.3.4 Step 2a: Price Prediction

As the DR approach optimizes a/c activation under consideration of expected electricity costs, the algorithm must integrate currently observable and expected future electricity (market) prices. Therefore, the DR approach requires an electricity price prediction model, which is not only accurate but also able to keep comprehensiveness and simplicity. Although different price prediction models are conceivable, the present paper builds upon the work of Fridgen, et al. (2016), who develop a discrete-time price prediction model for the valuation of LS flexibility in an intraday electricity market. In the following, their model is referred to as "price prediction model".

Within the price prediction model, the authors develop a stochastic process "which realistically replicates intraday electricity spot price development" (Fridgen, et al. 2016: p.537). Their stochastic process predicts electricity price movements and thereby certain reoccurring intraday patterns out of historical data. Since this paper does also focus on intraday flexibility in discrete-time increments, the price prediction model is appropriate for present purposes.

The price prediction model is a discretized version of a geometric Brownian motion consisting of two components: A component depicting expected price changes (drift) and a component depicting uncertain price changes (volatility). The computation of the drift integrates historical time (of day)-dependent mean electricity prices and expects that the process reverts to these patterns (mean-reversion). Since mean price and volatility patterns vary between different times (of day), the price prediction model ties a "chain of single-period stochastic processes" (Fridgen, et al. 2016: p.1001). However, the present paper makes some modifications to align the price prediction model: The original model values LS flexibility using a real options approach, since flexibility is purchased in these authors' scenario. Real options and their value are dependent on price volatility. Whereas Fridgen et al. (2016) model only electricity prices as the underlying asset to their real option, this paper would have to model both electricity prices and demand, which would result in a far more complex real option analysis. Instead, for a first approach, a simple expectation maximization on already existing flexibility is applied. Assuming risk-neutral building operators, price volatility is no influencing factor for ex-ante decision making:

Assumption 3. The decision maker is risk-neutral in his decision making.

The resulting electricity price prediction model based on Fridgen, et al. (2016) is defined by the following term (with S being the spot price for electricity, t being the time of day, $\theta \in [0,1]$ being the speed of mean-reversion, $\bar{\mathrm{S}}$ being the long-term mean electricity price, and $\alpha = \frac{\sum_{i=0}^{i=n} S(t-i)}{\sum_{i=0}^{i=n} \bar{S}(t-i)} \in [0, \infty)$ being a parameter for short-term adjustment of $\bar{\mathrm{S}}$): $S(t+1) = S(t) + \theta * \left(\alpha * \bar{S}(t+1) - S(t)\right)$. The speed of mean-reversion θ determines how fast the electricity price is expected to return to its long-term price pattern during the next discrete time increment. If $\theta = 1$, the electricity price in $t+1$ is expected to equal the adjusted long-term mean price in $t+1$. If $\theta = 0$, the electricity price in $t+1$ is expected to equal the price in t. The short-term adjustment α determines the adjustment of $\bar{\mathrm{S}}$ to represent recent price information. In particular, daily electricity prices usually deviate from their long-term mean price level because of temporary fluctuations in electricity demand and supply. The DR approach integrates current observable price information and applies the price prediction model whenever it must decide about a/c activation.

III.2.3.5 Step 2b: Demand Calculation

Besides electricity prices, building operator's electricity costs depend on electricity demand. In step 2b, the DR approach calculates electricity demand ($D(t_i, t_L, x)$) for a/c activation. $D(t_i, t_L, x)$ is defined as the total amount of electricity (in kwh) that is consumed by activating a/c between t_i and t_L. It depends (inter alia) on the difference between outside temperature and $\mathrm{temp_{req}}$, a subtraction which is referred to as $\Delta\mathrm{temperature(t)}$. For further analysis, $\mathrm{D(t_i, t_L, x)}$ is separated into two components (Figure III.2-5):

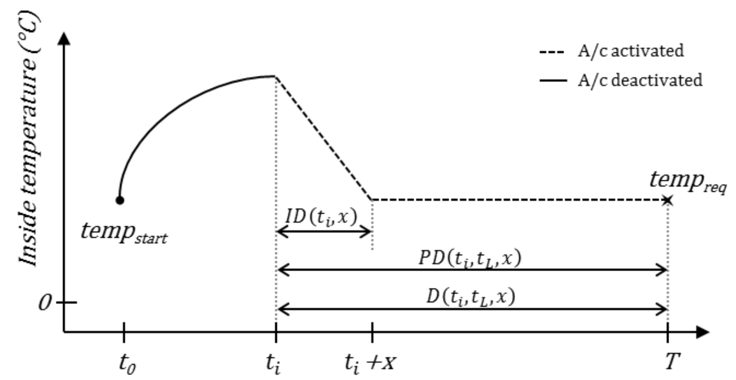


Figure III.2-5: Electricity demand in the applied procedure

$\mathrm{ID(t_i, x)}$ is the initial electricity demand or payback load (Illerhaus and Verstege 2000) for a/c deactivation in $\mathrm{t_0}$ and subsequent thermal movement until a/c (re)activation. $\mathrm{ID(t_i, x)}$ can be computed as $\sum_{\mathrm{t=t_i}}^{\mathrm{t=t_i+x-1}} \mathrm{ID(t)}$, i.e., $\mathrm{ID(t)}$ is the initial electricity demand per time increment. To estimate $\mathrm{ID(t)}$, building operators analyze the historical data-based dependence of $\mathrm{ID(t)}$ on previous periods' (e.g. hours') development of $\Delta\mathrm{temperature(t)}$. They regress $\mathrm{ID(t)}$, for example, on mean temperature since $\mathrm{t_0}$ or use a weighted average with higher weighting for more recent temperature developments (due to thermal movement). A multiple regression model that regresses $\mathrm{ID(t)}$ simultaneously on every previous periods' $\Delta\mathrm{temperature(t)}$ is also conceivable but exposed to great complexity and therefore data requirements. If historical data is absent, building operators could conduct experimental runs to collect the required information. Moreover, starting in $\mathrm{t_i}$, further electricity $\mathrm{PD(t_i, t_L, x)}$ is required to compensate for continuous thermal movement until T. After achieving $\mathrm{temp_{req}}$, $\mathrm{PD(t)}$ is the periodical amount of electricity (in kwh) that is required to keep $\mathrm{temp_{req}}$ between t and $\mathrm{t+1}$. In addition, until $\mathrm{temp_{req}}$ is achieved (i.e., during the initial cooling process between $\mathrm{t_i}$ and $\mathrm{t_i+x}$), there is already a fraction of $\mathrm{PD(t)}$ that is required (in addition to $\mathrm{ID(t_i, x)}$) as the a/c system starts to regulate the inside temperature toward $\mathrm{temp_{req}}$, which also initializes energy loss due to thermal movement. For simplification, this amount of energy is estimated by $\frac{\mathrm{PD(t)}}{2}$ for $\mathrm{t} \in [\mathrm{t_i}, \mathrm{t_i + x - 1}]$. Hence, $\mathrm{PD(t_i, t_L, x)}$ can be computed as $\sum_{\mathrm{t=t_i}}^{\mathrm{t_i+x-1}} \frac{\mathrm{PD(t)}}{2} + \sum_{\mathrm{t=t_i+x}}^{\mathrm{t=t_L}} \mathrm{PD(t)}$. Like $\mathrm{ID(t)}$, building operators can measure the dependence of $\mathrm{PD(t)}$ on $\Delta\mathrm{temperature(t)}$. Figure III.2-6 illustrates a schematic dependency structure for $\mathrm{PD(t)}$. Thus, the algorithm can compute total electricity demand between t_i and t_L: $D(t_i, t_L, x) = ID(t_i, x) + PD(t_i, t_L, x) = \sum_{t=t_i}^{t=t_i+x-1} ID(t) + \sum_{t=t_i}^{t=t_i+x-1} \frac{PD(t)}{2} + \sum_{t=t_i+x}^{t=t_L} PD(t)$.

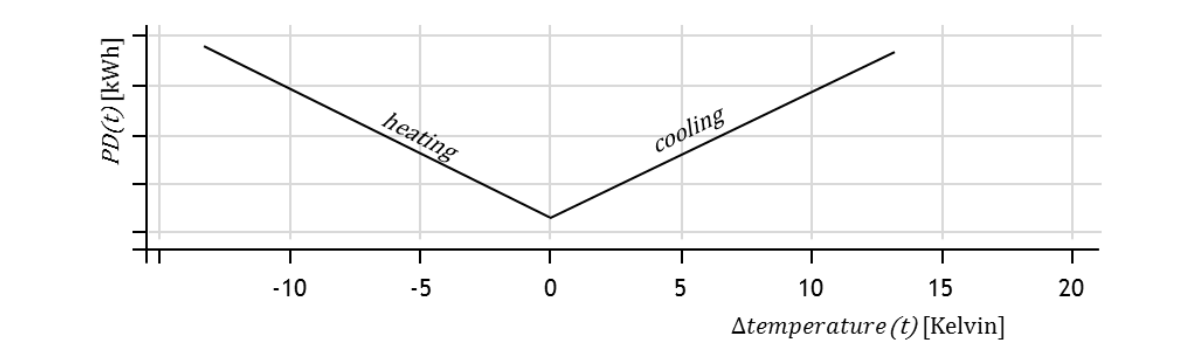


Figure III.2-6: Schematic dependence of $PD(t)$ on $\Delta temperature(t)$

III.2.3.6 Step 3: Decision-Making

In this step, the DR approach decides either to activate the a/c system in the current period or to defer the activation decision to the next period. More precisely, for each possible (discrete) activation time t_i until t_L, estimated in time t_m ($m \leq i$, refers to the current point in time for decision making), the algorithm calculates expected total electricity costs for a/c activation. For $ID(t_i, x)$ and $PD(t_i, t_L, x)$, costs amount to:

- $C(ID(t_i, x)) = \sum_{t=t_i}^{t=t_i+x-1} \big(ID(t) * S(t)\big)$
- $C(PD(t_i, t_L, x)) = \sum_{t=t_i}^{t=t_i+x-1} \left(\frac{PD(t)}{2} * S(t)\right) + \sum_{t=t_i+x}^{t=t_L} \big(PD(t) * S(t)\big)$

By adding $C(ID(t_i, x))$ and $C(PD(t_i, t_L, x))$, building operators can calculate expected total electricity costs $C(t_i, t_L, x)$. In particular, $C(t_i, t_L, x|t_m)$ expresses these costs estimated in time t_m. The objective of the algorithm in time t_m is therefore to identify the minimum $C(t_i, t_L, x|t_m)$ out of all possible activation times t_i, i.e. $\min_i(C(t_i, t_L, x|t_m))$. If the algorithm expects $\min_i(C(t_i, t_L, x|t_m)) = C(t_m, t_L, x|t_m)$, a/c is activated and ex-ante optimization is terminated. Otherwise, the algorithm defers the activation decision for one period to update information and to decide again. If $t_m = t_L$ is reached, a/c activation is obligatory.

III.2.3.7 Step 4: Feedback

In the last step, the activation decision and resulting electricity costs are ex-post evaluated. The algorithm's activation decision bases on electricity price and demand predictions and does not necessarily yield optimal results. Hence, there is a need to quantify electricity cost savings to evaluate the quality of the artifact (Goebel 2013; Strueker and Dinther 2012). Absolute and relative cost savings can be computed by comparison between the results of the applied procedure (Figure III.2-3) and a procedure with no DR. As reference for no DR ("default procedure"), procedure (3) from Figure III.2-2 can be applied in which a/c is activated continuously throughout the day. In addition, the feedback should contain a comparison between cost savings and cost savings potential. Cost savings potential is defined as the maximum of electricity costs that could have been saved within the applied procedure by optimally applying LS within the given flexibility window from an ex-post perspective. This is the benchmark for the DR approach. Finally, observable information can be recorded (e.g. time of day, electricity prices, outside temperature, and electricity demand) and processed into a continuously growing database that the DR approach can use to maintain or improve prediction quality.

III.2.4 Artifact Demonstration and Evaluation

III.2.4.1 Real-World Scenario Description

In this section, the artifact is evaluated as required within the DSR paradigm. Therefore, the artifact's functionality is illustrated within an example, i.e., the decision algorithm of LS is applied to demonstrate that the DR approach "can be implemented in a working system" (Hevner, et al. 2004: p.79). Afterward, the DR approach is evaluated with multiple simulations of random scenarios to demonstrate that the "artifact [generally] works and does what it is meant to do" (validity) (Gregor and Hevner 2013: p.351). For both, real-world data is applied.

The object that serves for demonstration and evaluation is located in the southeastern part of the United States, in Georgia. Georgia is known for its subtropical climate, with humid summers and moderate winters. Especially during summer months (May to September), temperatures are comparatively high (between 15°C - 31.7°C on average). During winter months (November to March), temperatures are on average above freezing point (between 0.6°C – 18.3°C). For research purposes at the University of Georgia, a/c data was collected from two University buildings. The rooms within the buildings are used as offices and for large meetings. Both buildings are partly open to the public. Using measuring points, different parameters were collected during a period ranging from January 2010 to December 2014. Collected parameters comprise inside temperature on a room level, outside temperature, and electricity consumption (kWh) for a/c usage. Measuring points recorded instantaneous, i.e., not as averaged values within a certain time span. Main components of the a/c system are two chiller systems that jointly air-condition via chilled water loops. Together, both chiller systems have a maximum wattage of 1.2 MW and are responsible for 90% of the a/c system's total electricity consumption. The remaining 10% are consumed by auxiliary equipment that scales up with the chillers' current load level. By applying variable load control, the a/c system is designed to provide a constant supply water temperature (about 5 °C +/- 0.2 °C). Electricity consumption of the a/c system depends on the temperature of return water (that, in turn, depends on outside and the buildings' inside temperature). Warmer return water increases electricity consumption and vice versa. To date, no DR mechanism is in place and the (central) a/c system runs all day (not to be confused with a single room's air supply, which can toggle on and off), even in times of low or no occupancy (e.g., on weekends and at night). Overall, the current system wastes energy and yields unnecessary electricity costs.

The University purchases electricity for the a/c system from a local utility company. The company charges real-time electricity prices rather than offering a flat plan. Thus, electricity prices are sometimes high and the University incurs significant electricity costs. The collected data of the a/c system and payed electricity prices make this example suitable for the DR approach's demonstration and evaluation. Although a data-driven DSS that integrates the DR approach is not implemented yet, its theoretical cost savings potential is evaluated in this scenario.

For variable load control, the a/c system already possesses sensor systems that measure further parameters such as supply water temperature and current load level, a web server that collects all sensor information, and a remote controller that building operators can access using a web portal. Access to the utility's real-time electricity prices is available by using the customer portal. To establish cost-sensitive a/c control, there is a need for changes and enhancements in the monitoring and control system as it must dynamically import the utility's price information (by accessing a respective application interface) and possess control software that applies the data-driven DR approach. Moreover, hardware for faster communication and computation would be useful in order that the system can react on changes in input information in near real-time (which is especially necessary to scale down time increment length between two optimization iterations). Due to an expert's opinion (an engineer at the university with a PhD who is specialized in a/c systems), the sum of all university-internal and -external costs for implementing such cost-sensitive control in the considered a/c system amounts to about

$100.000. Further running costs are expected to be insignificant low. Besides this application scenario, the expert expects the control software to be applicable in other university buildings as soon as they are also equipped with modern monitoring and control systems. However, as there is further need for clarification which other a/c systems are suitable and intended for upgrade, validly estimating respective economies of scales within this scenario is not possible to date. Hence, to obtain a conservative estimate, the present paper limits business case analyses to the described scenario.

III.2.4.2 Step 1: Scheduling (Demonstration)

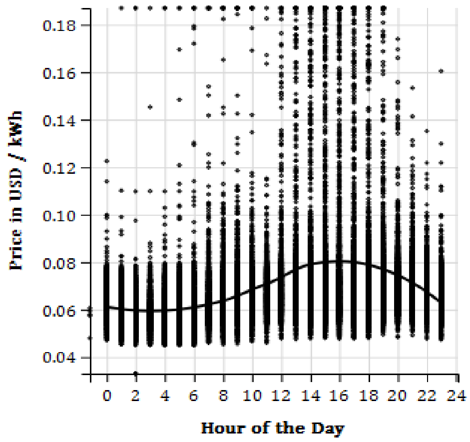
For artifact demonstration, $\mathrm{temp}_{\mathrm{req}}$ is set to 21°C. This is the currently targeted inside temperature in the scenario's buildings. As Georgia, USA, is known for its humid and hot summers, a typical day in September is chosen, when a/c is required to cool (keep) the inside temperature to (at) 21°C. In particular, the DR approach is applied on September 04, 2014. The hypothetical event of interest (e.g., a major event of a university initiative) takes place at 2pm (occupancy time) in both buildings. The earliest possible a/c activation is set to 7am. The University's expert stated that every room within the two buildings (regardless of current inside and outside temperature) can be cooled down to $\mathrm{temp}_{\mathrm{req}}$ by a/c within one hour. Hence, $\mathrm{t_L}$ is at 1pm (i.e., $\mathrm{x} = 1$). As the dataset of historically payed electricity prices features hourly time increments, artifact demonstration and evaluation is also conducted with hourly time increments between $\mathrm{t_0}$ and $\mathrm{t_L}$. Table III.2-1 illustrates the schedule.

Time	t_0*=7am*	*8am*	*9am*	*10am*	*11am*	12noon	t_L*=1pm*	*T=2pm*
t	0	1	2	3	4	5	6	7

Table III.2-1: Schedule for artifact demonstration

III.2.4.3 Step 2a: Price Prediction (Demonstration)

As described in Section III.2.3, this paper modifies and applies the price prediction model developed by Fridgen, et al. (2016). This price prediction model draws upon the existence of historical time of day- and season-specific price patterns and updates price prediction at every time step by integrating new observable price information. Figure III.2-7 illustrates historical time of day-specific price patterns of electricity prices. Further, Table III.2-2 illustrates descriptive statistics on electricity price patterns of different months.



	Mean	Std. Dev.	Min	Max
January	0.06983	0.03770	0.04693	0.67465
February	0.06509	0.00937	0.04756	0.11991
March	0.06392	0.00784	0.03000	0.10256
April	0.06467	0.00929	0.04483	0.11846
May	0.06460	0.00916	0.04661	0.17592
June	0.07623	0.03772	0.04643	0.42924
July	0.08093	0.04634	0.04800	0.41529
August	0.08153	0.05391	0.04981	0.72466
September	0.06680	0.01556	0.04919	0.31288
October	0.06406	0.00828	0.04600	0.09350
November	0.06387	0.00864	0.05137	0.30558
December	0.06414	0.01241	0.04933	0.36954

Figure III.2-7 (l.): Hourly mean electricity prices (June 2012 – November 2014)

Table III.2-2 (r.): Descriptive statistics for electricity prices per month [$/kWh]

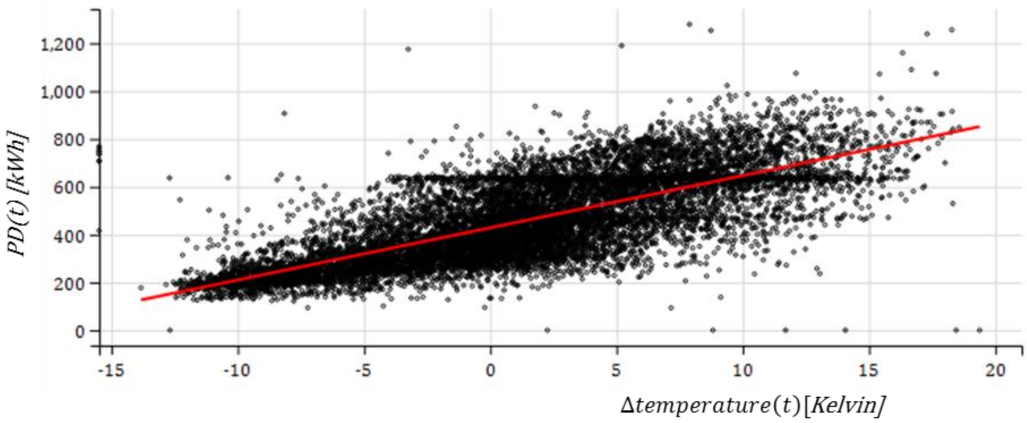
For configuration purposes, building operators can adjust three endogenous (model) parameters within the DR approach's price prediction model: θ, n (the adjustment reference interval to compute shot-term adjustment α), and an estimation corridor to compute $\bar{S}(t)$. Fridgen, et al. (2016) vary θ within an interval between 0 and 1. For artifact demonstration, θ is arbitrarily set to 1.0 and further analysis of its influence is left to the subsequent evaluation. Similar, n is set to 0. To calculate $\bar{S}(t)$, Fridgen, et al. (2016) analyze seasonal price patterns. The authors differentiate between summer, winter, and intermediate season. However, this does not fully reflect the course of historical time-of-day-specific price patterns. For example, their intermediate seasons include March – May and September – November. Therefore, March and September share the same $\bar{S}(t)$, which is (in our case) not accurate as shown in Table III.2-2. Hence, this paper calculates $\bar{S}(t)$ based on a historical corridor around the date of interest and time-of-day. For the presented example (September 04, 2014), $\bar{S}(t)$ at (e.g.) 12 noon is calculated by averaging previous-years' historical electricity prices from (e.g.) 30 days prior to 30 days after the date of interest, i.e., from August 05, (2010-2013) to October 04, (2010-2013) each of which at 12 noon. Table III.2-3 illustrates respective results (with S(t) being the actual observable electricity prices).

(i)	*Time (September 04, 2014)*	*7am*	*8am*	*9am*	*10am*	*11am*	*12noon*	*1pm*	*2pm*
(ii)	$\boldsymbol{t}$	0	1	2	3	4	5	6	7
(iii)	$\boldsymbol{\overline{S}(t)}$ *[$]*	0.0585	0.0608	0.0625	0.0643	0.0671	0.0732	0.0833	0.0959
(iv)	$\boldsymbol{S(t)}$ *[$]*	0.0606	0.0599	0.0639	0.0655	0.0676	0.0692	0.0708	0.0906
(v)	$\boldsymbol{\theta}$	1.0							
(vi)	$\boldsymbol{\alpha}$ $(\boldsymbol{n=0})$	0.9710	0.9901	0.9964	0.9805	0.9876	1.0246	1.1050	1.0991
(vii)	$\boldsymbol{E(S(t \mid 7am))}$ *[$/kWh]*	0.0606	0.0625	0.0644	0.0662	0.0690	0.0753	0.0857	0.0986
(viii)	$\boldsymbol{E(S(t \mid 8am))}$ *[$/kWh]*		0.0599	0.0632	0.0650	0.0677	0.0739	0.0841	0.0968
(ix)	$\boldsymbol{E(S(t \mid 9am))}$ *[$/kWh]*			0.0639	0.0646	0.0673	0.0734	0.0836	0.0962
(x)	$\boldsymbol{E(S(t \mid 10am))}$ *[$/kWh]*				0.0655	0.0684	0.0746	0.0849	0.0977
(xi)	$\boldsymbol{E(S(t \mid 11am))}$ *[$/kWh]*					0.0676	0.0741	0.0843	0.0970
(x)	$\boldsymbol{E(S(t \mid 12noon))}$ *[$/kWh]*						0.0692	0.0813	0.0935
(xi)	$\boldsymbol{E(S(t \mid 1pm))}$ *[$/kWh]*							0.0708	0.0858
(xii)	$\boldsymbol{E(S(t \mid 2pm))}$ *[$/kWh]*								0.0906

Table III.2-3: Price prediction parameters

III.2.4.4 Step 2b: Demand Calculation (Demonstration)

In the next step, the DR approach estimates $\mathrm{D}(\mathrm{t_i}, 1\mathrm{pm}, 1)$. As described in Section III.2.3.5, $\mathrm{D}(\mathrm{t_i}, 1\mathrm{pm}, 1)$ is split into $\mathrm{ID}(\mathrm{t_i}, 1)$ and $\mathrm{PD}(\mathrm{t_i}, 1\mathrm{pm}, 1)$ (as $\mathrm{x} = 1$ is constant within the real-world scenario, this section continues with a reduced formal notation that neglects x). For the real-world scenario, Table III.2-4 illustrates related $\Delta\mathrm{temperature}(\mathrm{t})$ and $\mathrm{PD}(\mathrm{t})$ observations and a respective linear regression.



Model parameters $\text{PD}(t)$ ~ $\Delta\text{temperature}(t)$				
	Estimate	*Standard error*	*t-value*	*Pr(>|t|)*
Intercept	428.5889	1.1151	384.3	2e-16 ***
$\Delta temperature(t)$	21.8235	0.1775	122.9	2e-16 ***
Significance codes	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Multiple R-squared	0.5645	Adjusted R-squared	0.5644	
F-statistic	1.511e+04	p-value	2.2e-16	

Table III.2-4: Empirical dependence of PD_{t_i} on $\Delta temperature$

The real-world scenario's a/c system is intended for cooling only. Cooling for $\Delta\text{temperature}(\text{t}) < 0$ implies that the two buildings were still heated up when outside temperature already fell below temp_{req}. Unfortunately, historical temperature forecasts that match the given historical data set were not obtainable. Hence, for artifact demonstration and evaluation, this paper requires an assumption to predict electricity demand:

Assumption 4. Actual outside temperature equals previous weather forecasts.

Generally, Assumption 4 depicts a great simplification of reality. However, since the DR approach focusses on short-term schedules for only a few hours, weather forecasts are close to reality (National Weather Service 2017). Moreover, subsequent evaluation integrates an artificial demand prediction error to analyze electricity cost savings' sensitivity to demand forecasting quality. Hence, the algorithm can use historical outside temperature as previous weather forecasts to compute $\text{PD}(\text{t})$. Table III.2-5 illustrates respective results.

(i)	*Time (September 04, 2014)*	*7am*	*8am*		*1pm*	*2pm*
(ii)	$\boldsymbol{t}$	0	1		6	7
(iii)	$\boldsymbol{Outside\ temperature(t)}$ $[°C]$	24.6	24.8		33.3	26.6
(iv)	$\boldsymbol{\Delta temperature(t)}$ *[K]*	3.6	3.8		12.3	5.6
(v)	$\boldsymbol{PD(t)}$ *[kwh]*	506.18	511.03	…	696.53	549.83
(vi)	$\boldsymbol{PD(t_i, 2pm)}$ *[kwh]*	4522.61	4014.01		898.10	274.92
(vii)	$\boldsymbol{ID(t_i)}$ *[kwh]*	0.00	202.47		1411.74	1690.35
(viii)	$\boldsymbol{D(t_i, 2pm)}$ *[kwh]*	4522.61	4216.48		2309.83	1965.27

Table III.2-5: Development of $\Delta temperature(t)$ and $PD(t)$

To date, as the presented a/c system runs all day, historically collected parameters are only appropriate for the estimation of $\mathrm{PD(t)}$ and therefore $\mathrm{PD(t_i, 12)}$. To precisely estimate $\mathrm{ID(t_i)}$, experimental runs would be necessary that analyze different a/c deactivation durations and different outside temperature developments. However, these experimental runs have not been conducted yet. As interim solution, threshold values are applied that logically contain the correct $\mathrm{ID(t_i)}$. For the lower limit applies: $\underline{\mathrm{ID}}(\mathrm{t_i}) = 0$, i.e., a situation in which no a/c is required to restore $\mathrm{temp_{req}}$. For the upper limit applies: $\overline{\mathrm{ID}}(\mathrm{t_i}) = \sum_{\mathrm{t=t_0}}^{\mathrm{t=t_i-1}} \mathrm{PD(t)}$, which equals the sum of all electricity that would have been necessary to keep the inside temperature at $\mathrm{temp_{req}}$ at any time since $\mathrm{t_0}$. Until more accurate solutions or historical data are available, $\mathrm{ID(t_i)} \in [0, \sum_{\mathrm{t=t_0}}^{\mathrm{t=t_{i-1}}} \mathrm{PD(t)}]$ is an appropriate interval to estimate $\mathrm{ID(t_i)}$. For demonstration, $\mathrm{ID(t_i)} = 0.4 * \sum_{\mathrm{t=t_0}}^{\mathrm{t=t_i-1}} \mathrm{PD(t)}$ is arbitrarily chosen, which simulates a building that absorbs heat to a medium extent. Table III.2-5 (vii) illustrates estimations for $\mathrm{ID(t_i)}$ and (viii) estimations for $\mathrm{D(t_i, 12)}$.

III.2.4.5 Step 3: Decision Making (Demonstration)

In the third step, the decision algorithm for LS determines if immediate a/c activation is ex-ante optimal (cost minimal). In particular, from the perspective of the current period, the algorithm predicts and compares expected total electricity costs for all possible activation periods. Table III.2-6 illustrates computations from the perspectives of 7am, 8am, 1pm, and 2pm. In this example, the algorithm would wait until 1pm to initialize a/c.

(i)	*Time (September 04, 2014)*	*7am*	*8am*	*10am*	*1pm*	*2pm*
(ii)	$\boldsymbol{S(t)}$ *[$/kWh]*	0.0606	0.0599		0.0708	0.0906
(iii)	$\boldsymbol{S(t\|7am)}$ *[$/kWh]*	0.0606	0.0625		0.0857	0.0986
(iv)	$\boldsymbol{S(t\|8am)}$ *[$/kWh]*	0.0549	0.0574		0.0636	0.0739
	…				…	
(v)	$\boldsymbol{S(t\|1pm)}$ *[$/kWh]*		0.0599		0.0841	0.0968
(vi)	$\boldsymbol{ID(t_i)}$ *[kwh]*	0.00	202.47		1411.74	1690.35
(vii)	$\boldsymbol{PD(t)}$ *[kwh]*	437.08	474.66	…	696.53	549.83
(viii)	$\boldsymbol{PD(t_i, 12)}$ *[kwh]*	4522.61	4216.48		2309.83	1965.27
(xi)	$\boldsymbol{C(t_i, 2pm\|7am)}$ *[$]*	325.63	316.18		172.48	187.76
(xii)	$\boldsymbol{C(t_i, 2pm\|8am)}$ *[$]*		300.43		201.27	190.24
(xiii)	$\boldsymbol{C(t_i, 2pm\|1pm)}$ *[$]*				156.98	168.60
(xiv)	$\boldsymbol{C(t_i, 2pm\|2pm)}$ *[$]*					163.12

Table III.2-6: Decision making within artifact demonstration

III.2.4.6 Step 4: Feedback (Demonstration)

In the last step, the DR approach ex-post evaluates the ex-ante chosen activation time as described in Section III.2.3.7. Therefore, the DR approach computes savings of its decision compared to the default procedure with no DR. By applying DR and activating a/c at 1pm, total electricity costs would have been $174.4. The default procedure, however, would have yielded total electricity costs of $312.80. This equals an electricity cost reduction of 44.25% due to the DR approach. Moreover, the theoretically optimal point in time for a/c activation (the benchmark) was also at 1pm. In particular, the DR approach was able to utilize the entire cost savings potential. Table III.2-7 summarizes the results for the presented example.

(i)	*Time (September 04, 2014)*	*7am*	*8am*	*9am*	*10am*	*11am*	*12am*	*1pm*	*2pm*
(ii)	$\boldsymbol{C_{ex-post}(t_i, 2pm)}$ *[$]*	312.8	294.3	276.2	253.8	228.5	201.7	174.4	178.1
(iii)	$\boldsymbol{C_{ex-post,realized}(t_i, 2pm)}$ *[$]*	174.4							
(iv)	$\boldsymbol{C_{ex-post,default}}$ *[$]*	312.8							
(v)	$\boldsymbol{C_{ex-post,Benchmark}}$ *[$]*	174.4							
(vi)	*Realized cost savings [%]*	44.23%							
(vii)	*Savings potential exploitation [%]*	100%							

Table III.2-7: Decision making within artifact demonstration

Since this example is biased in its validity because it was manually picked, the next section contains randomly chosen historical simulations and sensitivity analysis. Thereby, the general usefulness of the artifact is analyzed.

III.2.4.7 Evaluation

DSR methodology calls for evaluation of a developed artifact to provide evidence "how well the artifact supports a solution to the problem" (Peffers, et al. 2007: p.56). A possible evaluation method within DSR are simulations (Hevner, et al. 2004). This paper's evaluation is divided into three parts and presents historical simulations on the real-world scenario with 200,000 simulation runs each: The first part gives an impression on the DR approach's effectiveness in terms of average electricity cost savings and sensitivity of the latter to endogenous model parameters (θ, n, and estimation corridor, c.f. Section III.2.4.3). Subsequently, the triple of endogenous model parameters that yields the highest average electricity cost savings is fixed for the second part of the historical simulation. This calibration procedure for the prediction model is valid, as building operators can individually chose model parameters. The electricity cost savings of the second part are then analyzed on their sensitivity to exogenous scenario parameters (t_0, t_L, flexibility window length $t_L - t_0$, and dependency of ID_{t_i} on PD_t). To lift Assumption 4, a third simulation part integrates an artificial hourly demand prediction error (to a variable extent). Therefore, sensitivity of electricity cost savings to forecasting quality of electricity demand is measured. For all simulation parts, sensitivity of the results to the electricity market is analyzed by also repeating every simulation with electricity prices from the German-Austrian market area of EPEX SPOT. This market has a significantly growing capacity of renewable energy generation (EPEX SPOT 2017) that may evolve to a global trend. To isolate market influences on the results, the object and temperature conditions are assumed to equal the real-world scenario. In the following, this section refers to both markets as US market and EU market, respectively. Results of all simulation parts are discussed afterward.

III.2.4.7.1. Historical Simulation – Part 1

Parameter	*Values (intervals)*	
Simulation runs	200,000	
Date	{June 01, 2012,…,November 30, 2014}	Randomized
Starting time t_0	{6am,7am,…,6pm}	Randomized
Latest point for a/c activation t_L	{($t_0 + 1$),…,min(10pm, ($t_0 + 8$))}	Randomized
Theta θ	{0, 0.25, 0.5, 0.75, 1.0}	Randomized
Reference interval n [h]	{0, 2, 4, 6 no α }	Randomized
Estimation corridor for $\bar{S}$ [days]	{30, 60, 90}	Randomized
Initial Demand $ID(t_i)$ [kwh]	$\{0, 0.25 * \sum_{ü_0}^{t=t_i} \mathrm{PD}(t_i), \dots, 1.0 * \sum_{t=t_0}^{t=t_i} \mathrm{PD}(t_i)\}$	Randomized

Table III.2-8: Range of evaluation parameters (simulation - part 1)

Table III.2-8 illustrates evaluation parameters and their range. Simulation runs are conducted by sampling with replacement. Over all parameter combinations, the DR approach yields average electricity cost savings of $94.61 (or 44.52%) for the US market and €48.42 (or 44.07%) for the EU market compared to the default procedure with no DR. Standard deviation is $134.62 (142.29% of mean) for the US market and €52.30 (108.01% of mean) for the EU market. The cost savings potential (i.e., the benchmark) is $99.63 (or 46.88%) for the US market and €50.58 (or 46.03%) for the EU market. Therefore, the utilization of cost savings potential by applying the DR approach is 94.96% for the US market and 95.74% for the EU market. Table III.2-9 presents the result's sensitivity to endogenous model parameters:

	US market		*EU market*	
	Absolute savings	*Relative Savings*	*Absolute savings*	*Relative Savings*
Mean-reversion $\boldsymbol{\theta}$				
0	$92.36	43.47%	€48.25	43.80%
0.25	$93.41	44.19%	€47.90	43.77%
0.5	$95.45	44.78%	€48.37	43.98%
0.75	$95.62	44.96%	€48.66	44.37%
1	$96.22	45.19%	€48.94	44.41%
Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of ($\theta < 0.5$) ≥ mean savings of ($\theta \geq 0.5$), consequently higher θ preferable.				
Adjustment reference interval $\boldsymbol{n}$				
0h	$96.23	45.23%	€49.12	44.71%
2h	$95.13	44.61%	€48.83	44.45%
4h	$93.91	44.16%	€48.48	44.11%
6h	$93.38	44.06%	€48.24	44.01%
Off	$94.41	44.54%	€47.46	43.07%
Two-Sample t-Test: Reject H_0 hypothesis for European market (US -, EU ***) that mean savings of "short-term adjustment"≤ mean savings of "no short-term adjustment", consequently applying short-term adjustment preferable. Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of ($n \neq 0$) ≥ mean savings of ($n = 0$), consequently $n = 0$ preferable.				

Estimation corridor length				
30	\$94.47	44.54%	€48.29	44.07%
60	\$95.02	44.65%	€48.39	44.00%
90	\$94.34	44.37%	€48.58	44.13%
Two-Sample t-Tests: No significant preferences for both markets (US -, EU -)				
*** Significant for 1% level, ** significant for 5% level, * significant for 10% level				

Table III.2-9: Sensitivity of absolute and relative savings to endogenous (model) parameters

A multivariate sensitivity analysis identifies the triple of all three endogenous model parameters that yield (in combination) the highest average electricity cost savings: $\theta = 1.0$, $n = 6$h, and estimation corridor length $= 30$ days with average electricity cost savings of \$99.76 (or 45.40%) for the US market and $\theta = 1.0$, $n = 0$h, and estimation corridor length $=$ 60 days with average electricity cost savings of €51.28 (or 46.11%) for the EU market. As building operators can individually select endogenous model parameters, they should always conduct such pre-simulations on their individual historical data to maximize electricity cost savings. Thereby, as the present example illustrates, the best parameter combination can vary between different electricity markets. In the second part of the simulation, the respective best parameter combinations are fixed for both markets.

III.2.4.7.2. Historical Simulation – Part 2

Parameter	*Values (intervals)*	
Simulation runs	200,000	
Date	{June 01, 2012,…,November 30, 2014}	Randomized
Starting time t_0	{6am,7am,…,6pm}	Randomized
Latest point for a/c activation t_L	$\{(t_0 + 1)$,…,min(10pm, $(t_0 + 8))\}$	Randomized
Theta Θ	1.0 (both markets)	Fixed
Reference interval n [h]	6 (US), 0 (EU)	Fixed
Estimation corridor for $\bar{S}$ [days]	30 (US), 60 (EU)	Fixed
Initial Demand $ID(t_i)$ [kwh]	$\{0, 0.25 * \sum_{\text{ü}_0}^{t=t_i} PD(t_i), \ldots, 1.0 * \sum_{t=t_0}^{t=t_i} PD(t_i)\}$	Randomized

Table III.2-10: Range of evaluation parameters (simulation - part 2)

For the second evaluation part with fixed (calibrated) endogenous model parameters (cf. Table III.2-10), the DR approach yields average electricity cost savings of \$95.49 (or 45.03%) for the US market and €49.47 (or 45.14%) for the EU market compared to the default procedure with no DR. Standard deviation is \$132.81 (139.07% of mean) for the US market and €51.83 (104.75% of mean) for the EU market. The cost savings potential is \$99.84 (or 47.08%) for the US market and €50.61 (or 46.18%) for the EU market. Therefore, the utilization of cost savings potential by applying the DR approach is 95.65% (first evaluation part, without calibration, 94.96%) for the US market and 97.75% (first evaluation part 95.74%) for the EU market. Figure III.2-8 illustrates the histograms and Table III.2-11 presents the result's sensitivity to exogenous model parameters:

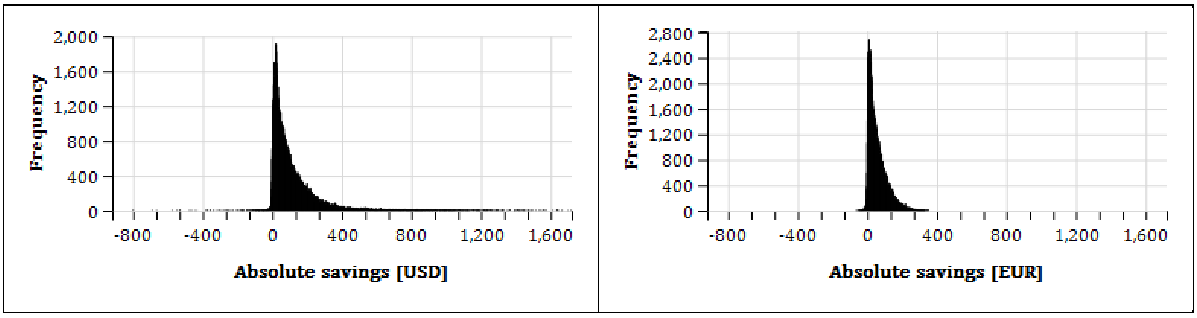


Figure III.2-8: Histogram of absolute savings (0 excluded, bin width: 1 [$ or €])

	US market		*EU market*	
	Absolute savings	*Relative savings*	*Absolute savings*	*Relative savings*
Starting time t_0				
6am	$58.74	39.17%	€44.67	44.40%
7am	$63.90	37.93%	€52.79	47.72%
8am	$73.00	37.64%	€59.18	49.51%
9am	$84.87	38.87%	€62.52	50.19%
10am	$98.04	40.05%	€60.87	48.24%
11am	$117.39	44.21%	€59.58	47.12%
12noon	$130.55	47.30%	€54.96	44.75%
1pm	$138.46	49.84%	€50.69	42.35%
2pm	$139.79	52.10%	€49.61	42.24%
3pm	$118.75	51.66%	€44.32	42.08%
4pm	$96.53	50.02%	€39.15	41.49%
5pm	$69.39	46.02%	€34.12	40.89%
6pm	$51.26	43.16%	€30.64	41.60%
Two-Sample t-Test: Reject H_0 hypothesis for US market (US ***) that mean savings of $(t_0 \leq 12am) \geq$ mean savings of $(t_0 > 12am)$, consequently late t_0 profitable. Two-Sample t-Test: Reject H_0 hypothesis for EU market (EU ***) that mean savings of $(t_0 > 12am) \geq$ mean savings of $(t_0 \leq 12am)$, consequently early t_0 profitable.				
Latest point for a/c activation t_L				
7am	$10.23	29.91%	€5.52	26.65%
8am	$16.27	35.58%	€9.76	30.25%
9am	$23.40	38.47%	€15.79	34.60%
10am	$33.07	40.47%	€24.82	40.22%
11am	$43.76	41.04%	€33.62	43.01%
12noon	$53.10	39.11%	€39.97	42.12%
1pm	$63.89	37.11%	€52.35	47.62%
2pm	$75.87	35.32%	€60.21	49.42%
3pm	$88.37	36.41%	€62.42	50.58%
4pm	$101.57	38.70%	€59.61	49.91%
5pm	$113.15	42.53%	€55.28	47.80%
6pm	$122.96	48.55%	€47.81	43.38%
7pm	$123.40	52.54%	€44.21	41.20%

8pm	\$130.34	53.07%	€48.40	40.03%
9pm	\$134.75	52.66%	€57.84	42.99%
10pm	\$138.70	52.36%	€68.40	46.93%
Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of $(t_L \leq 3pm) \geq$ mean savings of $(t_L > 3pm)$, consequently late t_L profitable.				
Flexibility window length $\boldsymbol{t_L - t_0}$				
1h	\$21.43	32.31%	€10.85	31.64%
2h	\$43.80	39.53%	€22.76	38.83%
3h	\$66.87	42.88%	€35.07	42.34%
4h	\$91.16	44.92%	€47.77	44.69%
5h	\$116.43	46.15%	€60.47	46.15%
6h	\$142.35	46.89%	€73.21	47.00%
7h	\$167.42	47.05%	€86.77	48.19%
8h	\$193.40	47.84%	€99.30	48.59%
Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of $(t_L - t_0 \leq 4) \geq$ mean savings of $(t_L - t_0 > 4)$, consequently longer flexibility window length preferable.				
Initial Demand $\boldsymbol{ID(t_i)}$				
0	\$188.93	89.12%	€97.39	89.03%
$\frac{1}{4} * \sum_{t=t_0}^{t=t_i} PD(t_i)$	\$140.93	66.49%	€73.46	66.81%
$\frac{1}{2} * \sum_{t=t_0}^{t=t_i} PD(t_i)$	\$90.11	42.67%	€48.49	44.44%
$\frac{3}{4} * \sum_{t=t_0}^{t=t_i} PD(t_i)$	\$44.25	20.74%	€23.41	21.24%
$\sum_{t=t_0}^{t=t_i} PD(t_i)$	\$11.91	5.62%	€3.91	3.57%
Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of $(ID(t_i) > 0.5 * \sum_{t=t_0}^{t=t_i} PD(t_i)) \geq$ mean savings of $(ID(t_i) \leq 0.5 * \sum_{t=t_0}^{t=t_i} PD(t_i))$, consequently lower $ID(t_i)$ preferable.				
*** Significant for 1% level, ** significant for 5% level, * significant for 10% level				

Table III.2-11: Sensitivity of absolute and relative savings to exogenous (scenario) parameters

III.2.4.7.3. Historical Simulation – Part 3

In the third evaluation part, Assumption 4 is lifted and an artificial hourly demand prediction error (DPE) is integrated. More precisely, for the first predicted discrete time step (i.e., hour), the DR approach estimates upcoming electricity demand by drawing from an equal distribution to the extent of the DPE around the historically measured value of that time. Predicting the subsequent discrete time step (i.e., the second hour in future), the algorithm reiterates this procedure but additionally adds the first hour's prognosis error. This approach is applied for all remaining discrete time steps within the temporal flexibility window.

Parameter	*Values (intervals)*	
Simulation runs	200,000	
Date	{June 01, 2012,…,November 30, 2014}	Randomized
Starting time t_0	{6am,7am,…,6pm}	Randomized
Latest point for a/c activation t_L	$\{(t_0+1),\ldots,\min(10pm, (t_0+8))\}$	Randomized
Theta Θ	1.0 (both markets)	Fixed
Reference interval n [h]	6 (US), 0 (EU)	Fixed
Estimation corridor for $\bar{S}$ [days]	30 (US), 60 (EU)	Fixed
Initial Demand $ID(t_i)$ [kwh]	$\{0, 0.2 * \sum_{t=t_0}^{t=t_i} PD_t, \ldots, 1.0 * \sum_{t=t_0}^{t=t_i} PD_t\}$	Randomized
Hourly Demand Prediction Error [DPE] (%)	{1, 5, 10, 30, 50}	Randomized

Table III.2-12: Range of evaluation parameters (simulation - part 3)

With fixed endogenous model parameters and DPE (cf. Table III.2-12), the DR approach yields average electricity cost savings of \$93.44 (or 44.10%) for the US market and €48.28 (or 44.01%) for the EU market compared to the default procedure with no DR. Standard deviation is \$132.40 (141.69% of mean) for the US market and €52.28 108.28% of mean) for the EU market. The cost savings potential is \$99.45 (or 46.94% compared to the default procedure) for the US market and €50.50 (or 46.04%) for the EU market. Therefore, the utilization of cost savings potential by applying the DR approach is 93.95% (second evaluation part 95.65%) for the US market and 95.60% (second evaluation part 97.75%) for the EU market. Table III.2-13 presents the result's sensitivity to the DPE:

	US market		*EU market*	
DPE	*Absolute savings*	*Relative savings*	*Absolute savings*	*Relative savings*
1%	\$94.86	44.89%	€49.48	45.12%
5%	\$94.68	44.62%	€49.15	44.75%
10%	\$95.23	44.96%	€48.86	44.66%
30%	\$93.18	43.87%	€47.75	43.50%
50%	\$89.29	42.19%	€46.19	42.04%

Two-Sample t-Test: Maintain H_0 hypothesis for both markets (US -, EU *) that mean savings of ($DPE \leq 10\%$) ≥ mean savings of "no DPE", consequently low DPE has no significant influence on results.
Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of ($DPE > 10\%$) ≥ mean savings of "no DPE", consequently high DPE has significant influence on results.
Two-Sample t-Test: Reject H_0 hypothesis for both markets (US ***, EU ***) that mean savings of ($DPE > 10\%$) ≥ mean savings of ($DPE \leq 10\%$), consequently lower DPE preferable.

*** Significant for 1% level, ** significant for 5% level, * significant for 10% level

Table III.2-13: Sensitivity of absolute and relative savings to hourly demand prediction error

III.2.4.7.4. Discussion of Evaluation Results:

Summarizing all evaluation results, the authors derive the following insights and interpretations: Within the real-world scenario, there is a huge savings potential in electricity costs by applying the DR approach. Thereby, the DR approach utilizes almost the entire cost savings potential, although it uses an algorithm with ex-ante (uncertain) electricity price prediction. The high exploitation of savings potentials is due to the following reasons:

- Electricity cost savings potential does only refer to cost savings that can (theoretically) be obtained by applying the present paper's applied a/c procedure (Figure III.2-3). It excludes further cost savings potential that would exist for more flexible but complex a/c procedures (e.g., "dynamic (de)activation" as illustrated in Figure III.2-2, (1)) or for managerial flexibility that differs from temporal flexibility (e.g., flexibility in temperature limits that this paper excluded by Assumption 1).
- Furthermore, for the second simulation part, early a/c activation (before $\mathrm{t_L}$) was ex-ante optimal in only 30.80% of all simulations for the US market and 25.63% for the EU market. More precisely, as this paper models hourly time increments within a real-world scenario that exhibits significant electricity demand to keep the inside temperature at $\mathrm{temp_{req}}$, it is often disadvantageous to cool before $\mathrm{t_L}$. The DR approach correctly anticipated that fact and had only few misjudgments. If this paper had modeled shorter time increments (e.g., quarter-hourly instead of hourly), more flexibility of action would (on the one hand) increase the DR approach's cost savings potential and (on the other hand) stronger challenge decision making (with possibly more misjudgments of the algorithm and therefore less exploitation of the savings potential). However, as the present paper's real-world example is restricted to hourly electricity market data (cf. Section III.2.4.2), a sensitivity analysis for time increment length is subject to future research.
- Besides, some electricity cost savings are due to Assumption 4, i.e., missing uncertainty in electricity demand forecasts. However, as the third simulation part and Table III.2-13 illustrates, this effect is rather small and has only a significant impact for huge misjudgments of the prediction model.
- Finally, the DR approach's performance within the presented real-world scenario is significant, since today's cost-insensitive a/c control wastes a huge amount of energy as a/c runs constantly throughout the day, even during disused hours on working days,

weekends, and night times. Therefore, smart a/c control that considers occupation schedules, electricity price prediction, and weather forecasts can yield huge electricity cost savings, even for minor misjudgments that fail ex-post optimal decision making.

The results also indicate that relative electricity cost savings, relative cost savings potential and the utilization of cost savings potential by applying the DR approach differ only slightly between the US and the EU market. This implies that the DR approach is applicable on different electricity markets that offer volatile electricity spot market prices. However, standard deviations of electricity cost savings are comparatively high and larger on the US market than on the EU market. The former results from the fact that average electricity cost savings depend on the simulation's (randomly chosen) model and scenario parameters (as illustrated within respective sensitivity analysis). As many parameter combinations are possible, electricity cost savings can vary significantly. In addition, the evaluation puts forth some implications of parameter sensitivity analysis:

- Sensitivity of electricity cost savings to endogenous (model) parameters: Significant greater electricity cost savings due to greater θ confirm the value of modeling mean-reversion to time-of-day-specific price patterns for short-term electricity prediction. While such patterns do not exist in many other spot markets (such as stock prices on capital markets) due to the instability of arbitrage opportunities, they occur in electricity spot markets as electricity consumption depends on time-dependent customer preferences that lack flexibility potential and renewable electricity generation that lacks controllability (cf. Introduction). Significant greater electricity cost savings due to the existence of an adjustment factor α that is computed on current observable price information ($n = 0$) indicates that instantaneous price developments are likely to deviate from long-term historical mean prices. Therefore, an appropriate prediction model should consider short-term effects on electricity market prices. As electricity cost savings did not significantly depend on estimation corridor length, historical time-of-day-specific price patterns on the two researched electricity markets are rather stationary, i.e., seasonal price patterns' influence on results are low.
- Sensitivity of electricity cost savings to exogenous (scenario) parameters: The observation that electricity cost savings for the US and the EU market significantly depend on t_0 and t_L is another indicator for the impact of both market's (individual) time-of-day-specific price patterns that help building operators to identify lucrative opportunities to utilize

flexibility in a/c. In addition, t_0 and t_L are critical influencing factors for available flexibility window length. The observation of longer flexibility window length significantly increasing electricity cost savings is intuitive, as a longer flexibility window (that is favored by low room or building occupancy) provides the DR approach with a greater economic scope of action. Similar, the dependency of electricity cost savings on $ID_{t_i}$is intuitive as buildings with less insulation are exposed stronger to (outside) temperature development and therefore thermal movement, which results in a higher payback load that shrinks electricity cost savings due to temporal a/c deactivation.

For the University of Georgia's business case calculation, the expert estimated total costs for implementing and running cost-sensitive a/c control (using the DR approach) to about \$100.000 (cf. Section III.2.4.1). Evaluation results illustrate that the payback period for this investment depends especially on electricity cost savings per LS measure and therefore on exogenous scenario parameters (as endogenous model parameters can be calibrated by the building operator). For discounting electricity cost savings, building operators require an appropriate annual risk-free interest rate r_f. Therefore, for example, they can calculate the mean of the 3-month U.S. Treasury Bill yields observed over the last 10 years, which would currently amount to $r_f = 0.7\%$ (Mukherji 2011; U.S. Department of Treasury 2017). Moreover, LS frequency is relevant, i.e., how often building operators can conduct LS measures. Applying a common net present value approach, Table III.2-14 shows calculations for the payback period of the business case (without economies of scales, cf. Section III.2.4.1) that authors use to support investment decision making within the described real-world scenario.

		Electricity cost savings per LS measure			
		\$40	\$80	\$120	\$160
Number of annual (equally distributed)	50	61.50	27.48	17.72	13.08
	100	27.48	13.08	8.59	6.40
	200	13.08	6.40	4.23	3.16
	365	7.02	3.47	2.30	1.72

Table III.2-14: Business case payback periods [Y]

III.2.5 Conclusion

The present research contributes to the development of data-driven DSSs that can significantly reduce building operators' electricity costs. In particular, a DR approach is presented, which utilizes existing LS flexibility potential of a/c systems by performing real-time decision making. The latter requires rapid information exchange and remote control for activating and deactivating a/c, which is enabled by using modern ICT (especially AMI).

The DR approach satisfies the requirements stated in the introduction: It is simple, general, and forward-looking. Computations are feasible without engineering expertise, because they focus on data-driven decision making. Building operators can use the presented four-step framework to derive their individual DR approach for real-estate a/c systems. The development of the DR approach follows principles of the DSR Paradigm. The artifact demonstration and evaluation propose that the DR approach is valid ("validity") (Gregor and Hevner 2013). By applying real-world data from two university buildings and a respective business case, the present paper demonstrates the usability of the artifact in practice ("utility") (Hevner, et al. 2004). Within the real-world scenario, the artifact would be able to yield remarkable electricity cost savings compared to current existing a/c procedure ("quality") (Gregor and Hevner 2013). However, sensitivity analysis illustrate that the payback period of the real-world business case does strongly depend on endogenous model and exogenous scenario parameters.

There are also limitations to the DR approach. First, an assumption is made that actual outside temperature equals previous temperature forecasts (i.e., there is no uncertainty in electricity demand). Although an artificial hourly demand prediction error is implemented to demonstrate that this assumption does only have little influence on results, future case studies on the general model should cut back this simplification. Second, this paper assumes a constant required room temperature $\mathrm{temp}_{\mathrm{req}}$ and therefore focuses on temporal flexibility of a/c systems. However, the possibility to generate further cost savings by considering flexibility in quality (i.e., flexibility of $\mathrm{temp}_{\mathrm{req}}$) is neglected and would be a promising extension for future research. Third, since authors have no data to estimate the dependence of initial a/c electricity demand on the previous hours' outside temperature development, only an interim solution is applied that basis on interval estimation. Fourth, the DR approach is limited to only one procedure of performing a/c. In particular, for reasons of simplicity, it cannot account for scenarios in which a building operator dynamically activates and deactivates the a/c system. A procedure that allows at each discrete time step to either activate or deactivate a/c and (for a/c activation) to control a/c intensity should further increase the cost savings potential. Fifth, there is also a proportion of simulation runs, in which cost savings are negative. To strengthen confidence, trust, and attention into DR technologies, future research should try to develop DR approaches that reduce the occasions of negative results. As negative results are more formative (Rozin and Royzman 2001), this might deter building o6perators to apply DR (Venkatesh, et al. 2003). Nevertheless, the designed artifact is a robust data-driven method for building operators and can be used beyond the application domain. By its simplicity, generality, and forward-look, it depicts a suitable solution for many applicants. In line with Palensky and Dietrich (2011), this is also a further step to make DSM more customer-centric in the future.

Acknowledgements

This research was (in part) carried out in the context of the Project Group Business and Information Systems Engineering of the Fraunhofer Institute for Applied Information Technology FIT. Furthermore, the authors would like to thank Richard T. Watson and Thomas Lawrence for their support, their data collection, data provision, and helpful advice.

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III.3 Research Paper 6: "Demand Side Management: Entscheidungsunterstützungssysteme für die flexible Beschaffung von Energie unter integrierten Chancen- und Risikoaspekten"

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Published in:	HMD - Praxis der Wirtschaftsinformatik, 55(3), 627-645

Abstract:

The German "energy transition" toward renewable energies exhibits an increase of volatility in energy supply and therefore threatens both grid stability and electricity price stability. Especially industrial companies meet the challenge to provide sufficient and affordable energy according to their individual production requirements. To this effect, the utilization of flexibility in these companies' energy demand and decentral energy generation ("demand side management") is a promising approach to realize cost savings and new profit opportunities on power exchanges, balancing power markets and specific forthcoming flexibility markets. However, the computation of available and economic energy flexibility potential is a highly complex task for industrial companies and literature has not yet delivered approaches on how to deal with that challenge. In this context, this paper motivates the development and application of new decision support systems that can be developed by industrial companies themselves or in cooperation with IT service providers and energy consultants with the objective to optimize the utilization of energy flexibility using an integrated risk and return management. Besides basics on energy flexibility and flexibility deployment, this paper presents important functional requirements for decision support systems in energy flexibility management. Subsequently, this paper presents a system architecture for such a decision support system and concludes with recommendations for practitioners. Thereby, practicability is ensured by presenting results from interviews with industry experts.

III.3.1 Die Energiewende in Deutschland

Im Jahre 2015 verständigten sich die Teilnehmer der UN-Klimakonferenz in Paris auf das Ziel, die globale Klimaerwärmung auf 2 °C im Vergleich zur vorindustriellen Zeit zu begrenzen und darüber hinaus eine Begrenzung von 1,5 °C anzustreben, um die Risiken des Klimawandels einzudämmen (United Nations 2015). Deutschland hat sich dabei mit ambitionierten Zielen zum Ausbau regenerativer Energieerzeugung eine Führungsrolle auferlegt, denn bis 2050 sollen 80% der Stromerzeugung erneuerbar sein (Bundesregierung 2017) und Treibhausgasemissionen um 80 bis 95% im Vergleich zu 1990 reduziert werden (Bundesregierung 2010). Der Großteil regenerativer Stromerzeugung soll dabei durch Photovoltaik- und Windkraftanlagen erfolgen, welche Wirtschaft, Politik und Gesellschaft vor zahlreiche neue Herausforderungen stellen. Die vermutlich größte Herausforderung ist die wetterbedingte Unkontrollierbarkeit und damit die erschwerte Prognose der Erzeugungsmengen dieser Anlagen. Während die Stromnachfrage einer naturgemäßen Volatilität unterliegt, können Energieversorger und Netzbetreiber bislang einen physischen Ausgleich v.a. durch fossile Kraftwerke (Gas, Kohle, Öl) und Kernkraftwerke schaffen, deren Ausbringungsmenge steuerbar ist. Die Ausbauziele von Photovoltaik- und Windkraftanlagen, der geplante Atomausstieg bis 2022 und der angestrebte Rückbau von Kohlekraftwerken im Hinblick auf die genannten CO_2-Ziele werden jedoch dazu führen, dass Prognoseunsicherheit in der Stromnachfrage auf steigende Prognoseunsicherheit (Volatilitäten) in der Stromerzeugung trifft, wodurch Versorgungs- und Preisrisiken in Deutschland, v.a. für Industrieunternehmen (IU), ansteigen. Um diesen Herausforderungen zu begegnen, werden seit September 2016 in den vier „Kopernikus-Projekten für die Energiewende“ des Bundesministeriums für Bildung und Forschung (mit einem Fördervolumen von jeweils bis zu 100 Mio. Euro über 10 Jahre) verschiedene Lösungsansätze entwickelt (BMBF 2017):

1. Intelligente Steuerung und Ausbau vorhandener Netzstrukturen
2. Speicherung von Überschüssen aus Photovoltaik- und Windkraftanlagen durch Power-to-X Technologien
3. Flexibilisierung des (industriellen) Energieverbrauchs

Der vorliegende Beitrag setzt insbesondere am dritten Punkt an. Mit der Flexibilisierung des Bezugs externer Energie(-träger) können IU einen wesentlichen Beitrag dazu leisten, Stromnetze und Strompreise zu stabilisieren und damit den Unsicherheiten durch vermehrt regenerative Energieerzeugung entgegenzuwirken. IU können diese Energieflexibilität bereits heute durch Handel an Märkten für Energie und Systemdienstleistungen entweder zur Reduktion von Energiekosten oder zur Generierung zusätzlicher Erlöse nutzen. Insbesondere ist der Markt für industrielle Energieflexibilität die letzten Jahre erheblich gewachsen (Reger und Kosch 2017). Die Wirtschaftlichkeit von Energieflexibilitätsmaßnahmen sollte aufgrund der Energiewende und den damit verbundenen (oben beschriebenen) Effekten in Zukunft weiter ansteigen. Dennoch existieren wesentliche Hindernisse, die IU bislang häufig von der Nutzung ihrer Energieflexibilität abhalten: *Erstens* kann die Nutzung von Energieflexibilität komplexe Opportunitätskosten erzeugen, welche bei IU für Verunsicherung darüber sorgen, ob und in welchem Rahmen die Nutzung von Energieflexibilität rentabel ist. *Zweitens* erfordert die effiziente und effektive Nutzung von Energieflexibilität die Einbindung zahlreicher unternehmensinterner Stakeholder und die Schaffung eines EFMs, welches nach klaren Vorgehensweisen und Verantwortlichkeiten verlangt. *Drittens* fehlt (insbesondere kleineren) IU häufig die notwendige Expertise und Investitionsbereitschaft, um ein wirksames EFM aus eigenen Kräften aufzubauen.

Ziel des vorliegenden Beitrags ist daher die Konzeption einer Systemarchitektur für ein künftiges Entscheidungsunterstützungssystem, welche IU bei der bestmöglichen Nutzung von Energieflexibilität zur Senkung von Energiekosten und Generierung von Erlösen unterstützt. Der Einsatz von Informationssystemen soll dabei insbesondere Unterstützung bei der Ermittlung des verfügbaren wirtschaftlichen Energieflexibilitätspotentials bieten und eine optimale Verwendung dessen durch Handlungsempfehlungen und/oder Automatisierung ermöglichen. Die systemtechnische Integration mehrerer Unternehmensbereiche der Energieversorgung und des Energieverbrauchs soll die Kommunikation zwischen verschiedenen unternehmensinternen Stakeholdern erleichtern und eine unternehmensweite Optimierung ermöglichen. Die vorgestellte Systemarchitektur dient IU als wesentliche Grundlage dafür, dass diese selbstständig oder gemeinsam mit ihren IT- und Energiedienstleistern ein individuelles EUS für ein datengetriebenes EFM unter integrierten Chancen- und Risikoaspekten entwickeln können. Zukünftig könnten diese EUS in übergeordneten Energiemanagementsystemen implementiert werden. Nach der Vorstellung einiger Grundlagen zum Thema Energieflexibilität und Flexibilitätsvermarktung erfolgt die Vorstellung funktionaler Anforderungen und der Systemarchitektur für ein datengetriebenes EFM. Zur Sicherstellung der Praxistauglichkeit werden dabei drei Experteninterviews miteinbezogen und am Ende einige Handlungsempfehlungen für die Praxis abgeleitet, die insbesondere für unerfahrene IU hilfreich sein können.

III.3.2 Energieflexibilität in Industrieunternehmen

Am 29. August 2016 hat die Bundesregierung das Gesetz zur Digitalisierung der Energiewende verabschiedet, welches u.a. „die Ausstattung von Messstellen mit intelligenten Messsystemen und modernen Messeinrichtungen" regelt (BMWi 2017). Dieses unter der Bezeichnung „Smart Meter Rollout" bekannt gewordene Gesetz fordert, dass ab 2017 alle Messstellen mit einem Jahresstromverbrauch von über 10.000 Kilowattstunden (d.h. fast alle IU) mit einem intelligenten Messsystem ausgestattet werden müssen. Obwohl IU damit jährlich um bis zu 130 € brutto mehr belastet werden, dient diese Technologie als eine wesentliche Grundvoraussetzung für diverse Energiedienstleistungen, z.B. zur Nutzung von Energieflexibilität (Reger und Kosch 2017).

Im Kontext dieses Beitrags bezeichnet Energieflexibilität allgemein die Fähigkeit eines IU, die Nachfrage nach extern bezogener Energie bzw. Energieträgern zeitlich flexibel zu steuern. Energieflexibilität kann in IU dabei auf zwei Arten existieren: **Zeitflexibilität**, d.h. temporale Verschiebung der Nutzung von externen Energie(-trägern) durch Energieverbraucher (in vor- oder nachgelagerte Zeitperioden) und **Produktflexibilität**, d.h. Wechsel eines Energieträgers bzw. einer Energieform, sodass Energieflexibilität ohne Beeinträchtigung der Endenergieverbraucher möglich ist. Die Nutzung von Energieflexibilität wird in Wissenschaft und Praxis auch als Lastmanagement oder Demand Side Management (DSM) bezeichnet. Dort wird DSM häufig in Bezug auf Strom definiert: DSM „bezeichnet die Anpassung der Stromnachfrage z.B. eines Unternehmens in Abhängigkeit von der Situation im Stromversorgungssystem. Der jeweilige Stromverbraucher erhält ein externes Signal, bspw. ein Preissignal, und passt daraufhin seine Stromnachfrage im Sinne der überbetrieblichen Anforderungen kurzfristig an" (dena 2013). In diesem Beitrag soll der Begriff DSM neben dem flexiblen Bezug von Strom auch den flexiblen Bezug von Fernwärme und fossilen Energieträger umfassen. Das Potential für Energieflexibilität (und damit DSM) entsteht v.a. in den folgenden Bereichen eines IU:

1. **Energiebeschaffung und -vermarktung:** V.a. energieintensivere IU haben üblicherweise eine eigene Beschaffungs- und Vermarktungseinheit für Energie(-träger). Sobald für letztere kein Einheitstarif existiert, d.h. marktpreisorientierte anstatt fixe Energiepreise entrichtet werden müssen, können (v.a. auf dem Strommarkt) kurzfristige Preisspitzen eine besondere Relevanz besitzen, welche den Wert vorhandener Energieflexibilität erhöhen. Dies ist v.a. dann der Fall, wenn für das IU direkter Zugang zu Märkten für Strom oder Systemdienstleistungen besteht.
2. **Kraftwerks- und Speichereinsatzplanung:** Wenn IU über eine eigene (dezentrale) Eigenenergieversorgung (z.B. Blockheizkraftwerke mit Gasmotoren oder Gasturbinen) oder Speichersysteme (z.B. Batteriespeicher, Wärmespeicher) verfügen, dann erhöhen diese Einheiten das Potential der Energieflexibilität. Insbesondere kann damit der Bezug externer Energie(-träger) ohne Beeinträchtigung des Endenergieverbrauchs flexibilisiert werden (Produktflexibilität).
3. **Verbrauchs- bzw. Produktionssteuerung:** Energieverbraucher (v.a. Produktionsanlagen) haben dann Energieflexibilität (Zeitflexibilität), wenn diese nicht durchgehend gemäß einem vordefinierten Fahrplan betrieben werden müssen. Insbesondere hochfrequentierte und verschieb- bzw. unterbrechbare („Batch-“)Prozesse bieten häufig Potential für Zeitflexibilität, da deren zeitlich vor- bzw. nachgelagerte Durchführung keine unmittelbaren Auswirkungen auf die angrenzenden Prozessschritte haben muss.

Beim Aufbau eines EFMs sollten Methoden und Prozesse definiert werden, die das Energieflexibilitätspotential der genannten Bereiche für unterschiedliche Zeithorizonte quantifizieren können. Dabei sollten sinnvolle Annahmen und Rahmenbedingungen getroffen werden, um das vorhandene Potential nicht zu über- oder unterschätzen. Eine sinnvolle Eingrenzung des Energieflexibilitätspotentials könnte im ersten Schritt dahingehend erfolgen, dass keine reputationsschädlichen Lieferverzögerungen, Produktqualitätseinbußen, Beschädigungen der Produktionsanlagen oder Konflikte mit Arbeitnehmern und Gesetzen eintreten dürfen. Vielmehr sollte das Energieflexibilitätspotential so erfasst werden, dass IU die entsprechenden Maßnahmen praktisch auch tatsächlich durchführen können. Dieses Potential wird im Folgenden **„technisch-organisatorisches Energieflexibilitätspotential“** genannt. Der Teil des technisch-organisatorischen Energieflexibilitätspotentials, dessen Nutzung aus Unternehmenssicht ökonomisch sinnvoll ist, wird im Folgenden als

„wirtschaftliches Energieflexibilitätspotential“ bezeichnet. Wirtschaftliche Energieflexibilität setzt voraus, dass die Kosten einer Energieflexibilitätsmaßnahme durch (erwartete) Energiekosteneinsparungen (bzw. Erlöse aus der Flexibilitätsvermarktung) überkompensiert werden.

III.3.3 Flexibilitätsvermarktung

IU können vorhandene Energieflexibilität bereits heute umfangreich vermarkten. Eine Zusammenfassung der bedeutsamsten Möglichkeiten für die Vermarktung industrieller Energieflexibilität wurde beispielsweise von Bertsch et al. (2017) im Zuge des Kopernikus-Projektes „SynErgie“ erstellt. Diese sind in Tabelle III.3-1 aufgeführt.

Energy-Only-Märkte	**Märkte für Systemdienstleistungen**
Terminmarkt (z.B. EEX Power Derivatives, OTC)	Regelleistungsmarkt (Übertragungsnetzbetreiber)
Day-Ahead-Markt (z.B. EPEX Spot, OTC)	Abschaltbare Lasten (Übertragungsnetzbetreiber)
Intraday-Markt (z.B. EPEX Spot, OTC)	Zuschaltbare Lasten (Übertragungsnetzbetreiber)

Tabelle III.3-1: Vermarktungsmöglichkeiten für Energieflexibilität

Während auf einem Energy-Only-Markt nur tatsächliche Stromlieferungen bis kurz vor ihrer physischen Lieferung gehandelt werden, wird auf einem Markt für Systemdienstleistungen zwischen der Vorhaltung von Leistung sowie ihrem tatsächlichen Abruf unterschieden.

Die verschiedenen Energy-Only-Märkte haben dabei eine feste zeitliche Reihenfolge (Bertsch et al. 2017): Am Terminmarkt werden Produkte lang- bis mittelfristig gehandelt (z.B. bis zu sechs Jahre im Voraus an der EEX Power Derivatives), am Day-Ahead-Markt für den darauffolgenden Tag und am Intraday-Markt bis kurz vor physischer Lieferung (z.B. 30 min an der EPEX Spot für den deutschen Raum). Beim Börsenhandel unterscheiden sich zudem die angebotenen Produkte (EEX 2017): Am Terminmarkt werden v.a. Futures und Optionen gehandelt (d.h. standardisierte Verträge, welche die zu liefernde Energiemenge, die Lieferperiode sowie den Preis spezifizieren), wobei die Ausübung der Verträge bei Futures eine Pflicht und bei Optionen (für den Käufer) ein Recht (ohne Ausübungszwang) darstellen. Die Lieferperioden reichen dabei von einzelnen Tagen bis hin zu ganzen Jahren. Dagegen werden am Day-Ahead-Markt Kontrakte gehandelt, die eine Lieferperiode für einen ganzen Tag (Baseload), für die Haupthandelszeit (Peakload, nur werktags von 9 bis 20 Uhr) oder für einzelne Stunden spezifizieren. Der Intraday-Markt ergänzt weitere, feingranulare Produkte (z.B. 15-Minuten-Kontrakte an der EPEX Spot für den deutschen Raum). Die Teilnahme am Börsenhandel setzt unter anderem eine technische Anbindung an die Handelssysteme, ein haftendes Eigenkapital von mindestens 50.000 €, die Fortbildung von Mitarbeitern zu EEX-Börsenhändlern und die Anerkennung als Handelsteilnehmer durch die European Commodity Clearing AG voraus (EEX 2017). Im OTC-Handel gelten dagegen individuelle Vereinbarungen.

Während die Teilnahme an Energy-Only-Märkten über Börsenanbieter oder OTC möglich ist, werden die Märkte für Systemdienstleistungen in Deutschland grundsätzlich von den vier Übertragungsnetzbetreibern (50 Hertz, Amprion, TenneT und Transnet BW) betrieben. Diese haben die Aufgabe, „das Leistungsgleichgewicht zwischen Stromerzeugung und -abnahme in ihrer Regelzone ständig aufrecht zu erhalten“ (Netzregelverbund 2017). Der Einsatz der Regelleistung liegt in der zeitlichen Abfolge nach dem Ende des Intraday-Handels, d.h. zum Zeitpunkt der physischen Lieferung. Damit soll ein passgenauer Ausgleich von Stromangebot und -nachfrage ermöglicht werden, welcher zur Wahrung der Netzstabilität bzw. der Sollfrequenz von 50,0 Hertz im Netz von Nöten ist (Bertsch et al. 2017). Es existieren drei Regelleistungsarten (Primärregelleistung, Sekundärregelleistung, Minutenreserveleistung), die sowohl mit positiver (Abschaltung) als auch mit negativer (Zuschaltung) Leistung zur Stabilisierung der Stromnetze beitragen und separat gehandelt werden. Die drei Regelleistungsarten unterscheiden sich v.a. hinsichtlich der Anforderungen an Abrufdauer, Aktivierungszeit, Mindestleistung und Steuerung, weswegen Flexibilitätsanbieter vorab jede Erzeugungs- und Verbrauchsanlage, die am Regelenergiemarkt teilnehmen soll, separat präqualifizieren müssen (Netzregelverbund 2017). Prinzipiell gilt, dass die Präqualifikationsanforderungen für die Primärregelleistung am höchsten und für die Minutenreserveleistung am niedrigsten sind. Bertsch et al. (2017) haben die wichtigsten Präqualifikationsanforderungen zusammengefasst (siehe Tabelle III.3-2).

	Primärregel-leistung	**Sekundärregel-leistung**	**Minutenreserve-leistung**
Abrufdauer	bis zu 15 Min	30 Sek bis 15 Min	15 Min bis mehrere h
Aktivierungszeit	maximal 30 Sek	maximal 5 Min	maximal 15 Min
Mindestleistung	1 MW	5 MW	5 MW
Steuerung	vollautomatisch	vollautomatisch	manuell

Tabelle III.3-2: Wichtige Präqualifikationsanforderungen

Für die industrielle Energieflexibilität eignen sich aufgrund dieser Anforderungen v.a. die Sekundärregelleistung und die Minutenreserveleistung (Bertsch et al. 2017). Die Vergütung erfolgt dabei über einen Leistungspreis (für die Bereitstellung einer Anlage) und einen Arbeitspreis (für deren tatsächlichen Abruf). Über regelmäßige Auktionen wird bestimmt, welche Flexibilitätsanbieter für die Bereitstellung und den Abruf der Regelenergie zum Zuge kommen. Obwohl die Eintrittsbarrieren für diese beiden Regelleistungsmärkte in den letzten Jahren gesunken sind (und auch im kommenden Jahr durch Neuregelungen weiter sinken werden), waren gleichzeitig fallende durchschnittliche Leistungspreise (aufgrund des zunehmenden Flexibilitätsangebots) ein Hemmnis (Next Kraftwerke 2017). Die in der Einleitung beschriebenen, steigenden Volatilitäten der deutschen Stromerzeugung könnten jedoch die Erlösmöglichkeiten durch Teilnahme an Regelleistungsmärkten künftig wieder steigern, da die höhere Planungsunsicherheit durch PV- und Windkraftanlagen zu mehr Abweichungen von Stromangebot und -nachfrage zum Zeitpunkt der physischen Stromlieferung führen wird. Die Verordnung über Vereinbarungen zu abschaltbaren Lasten (AbLaV) eröffnet eine weitere Vermarktungsmöglichkeit für Energieflexibilität, die vergleichbar mit dem Markt für positive Regelenergie ist. Es wird zwischen sofort abschaltbaren Lasten (Aktivierungszeit maximal 350 Millisekunden durch Frequenzmessung vor Ort) und schnell abschaltbaren Lasten (Aktivierungszeit maximal 15 min) unterschieden, wobei u.a. eine Abrufdauer von mindestens einer Viertelstunde bis maximal acht Stunden am Stück sowie mindestens vier Stunden pro Woche, eine technische Mindestverfügbarkeit von 552 Viertelstunden je Ausschreibungszeitraum (Woche), eine Mindestleistung von 5 MW und eine vollautomatische Steuerung bei Abruf vorausgesetzt werden (Next Kraftwerke 2017). Flexibilitätsanbieter schließen einen bilateralen Rahmenvertrag mit dem jeweiligen Übertragungsnetzanbieter und können anschließend an wöchentlichen Ausschreibungen teilnehmen (Netzregelverbund 2017). Betreiber von Anlagen der Kraft-Wärme-Kopplung (KWK) können überdies von einer Neuregelung im Energiewirtschaftsgesetz zu zuschaltbaren Lasten profitieren. Seit dem 1. Januar 2017 können diese mit den Übertragungsnetzbetreibern vereinbaren, dass im Falle von Netzengpässen die Stromeinspeisung aus KWK-Anlagen reduziert und zur Aufrechterhaltung der benötigten Wärmeversorgung zusätzlich Strom durch Power-to-Heat-Anlagen aus dem öffentlichen Netz verbraucht wird (Bertsch et al. 2017).

Des Weiteren sind in Zukunft spezielle Flexibilitätsmärkte geplant, was beispielsweise im Kopernikus-Projekt „SynErgie“ derzeit erarbeitet wird. Dabei sollen die oben genannten Märkte für Strom und Systemdienstleistungen an eine digitale Energie-4.0-Plattform angebunden werden und langfristig auch regionale Energieflexibilitätsprodukte anbieten.

III.3.4 Energieflexibilitätsmanagement durch Entscheidungsunterstützungssysteme

Für die IT-gestützte Umsetzung eines EFMs können IU auf Entscheidungsunterstützungssysteme (EUS) zurückgreifen, d.h. auf „interaktive, computerbasierte Systeme, die darauf abzielen, Entscheidungsprozesse zu unterstützen und die Qualität von Entscheidungen zu verbessern“ (Hrastnik et al. 2013). Diese sollten zur Komplexitätsreduktion in vorhandene oder neue übergeordnete Energiemanagementsysteme als Teilsystem integriert werden. Abhängig vom Automatisierungsgrad bzw. den Befugnissen des Systems, Steuerungsmaßnahmen selbstständig einzuleiten, handelt es sich dabei um konventionelle oder organische EUS. Konventionelle EUS stellen den menschlichen Entscheider und dessen alleinige Entscheidungsgewalt in den Vordergrund, während organische EUS Kompetenzen zur selbstständigen Optimierung und Steuerung besitzen (Strohmaier und Rollett 2005). Hinter letzteren Systemen steht das sog. Organic Computing. Gemäß dieser Disziplin steht die Schaffung teilautonomer, adaptiver und robuster Informationssysteme im Vordergrund (ähnlich dem situationsabhängigen Verhalten von Lebewesen, daher „organisch“), welche dynamisch den Rahmenbedingungen und Zielvorgaben menschlicher Entscheidungsträger folgen. In diesem Zusammenhang ist auch von gesteuerter Selbstorganisation („controlled self-organisation“) die Rede (Branke et al. 2006).

Bevor eine geeignete Systemarchitektur eines EUSs für das EFM konzeptioniert werden kann, müssen zunächst wesentliche funktionale Anforderungen definiert und evaluiert werden. Hierzu wurde ein Vorschlag des Autors erstellt, der anschließend mithilfe von drei Experten im Rahmen persönlicher Interviews auf dessen Praxistauglichkeit hin überprüft und ergänzt wurde. Das Ergebnis ist in Tabelle III.3-3 dargestellt.

Anforderung	**Beschreibung**
Backtesting- bzw. Lernfähigkeit	Das EUS sollte Prognosen und Entscheidungen evaluieren und Anpassungen am zukünftigen Prognose- und Entscheidungsverhalten vornehmen können.
Berechnung des technisch-organisatorischen Energieflexibilitätspotentials	Das EUS sollte basierend auf den erfassten Inputinformationen die Energieflexibilität berechnen können, welche unter technischen und organisatorischen Rahmenbedingungen zur Verfügung steht.
Berechnung des wirtschaftlichen Energieflexibilitätspotentials	Das EUS sollte die Teilmenge des technisch-organisatorischen Energieflexibilitätspotentials, welche wirtschaftlich ist, berechnen und als Grundlage zur Entscheidungsfindung nutzen können.
Erfassung Status quo Energieversorgung und -verbrauch sowie deren Abhängigkeiten	Das EUS sollte den Status und die Abhängigkeiten aller betrachteten Energieerzeuger, Energiespeicher und Energieverbraucher sowie aktuelle Preise und Beschaffungsinformationen aus Märkten für Energie, Systemdienstleistungen und Flexibilität erfassen können.
Flexibilitätsprognose	Das EUS sollte sowohl das technisch-organisatorische als auch das wirtschaftliche Energieflexibilitätspotential prognostizieren können.
Speicherung von Informationen	Das EUS sollte alle erfassten und berechneten Informationen in Zeitreihen abspeichern und für Prognose- und Backtesting-Zwecke nutzen können.
Steuerung von Energieversorgung und -verbrauch	Das EUS sollte Schnittstellen zu Märkten für Energie, Systemdienstleistungen und Flexibilität besitzen und selbstständig handeln (Empfehlungen geben) können, Schnittstellen zu Energieerzeugern und -speichern besitzen und diese selbstständig steuern (Empfehlungen geben) können und Schnittstellen zu Energieverbrauchern besitzen und diese selbstständig steuern (Empfehlungen geben) können.
User-Interface	Das EUS sollte zur Laufzeit Analysen und die Einstellung von Zielvorgaben und Rahmenbedingungen durch Nutzer erlauben.
Wirtschaftliche Optimierung	Das EUS sollte Steuerungsmaßnahmen (Handlungsempfehlungen) mit dem Ziel der erwarteten Kostenminimierung / Erlösmaximierung einleiten.

Tabelle III.3-3: Funktionale Anforderungen an EUS im EFM

Experte A ist Leiter des Energieeinkaufs eines IU der Chemie-/Keramikindustrie. Experte B ist „Head of Energy Operations“ eines IU der Papierindustrie. Experte C ist Berater für Optimierungssysteme in einem IT-Unternehmen, das Software-Lösungen für die Energiewirtschaft anbietet. Im Rahmen der Interviews haben Experte A und Experte B zur Aufnahme der „Backtesting- bzw. Lernfunktionalität“ geraten. Da sich IU häufig in einem dynamischen Umfeld befinden, muss ein solches System die Fähigkeit besitzen, sich auf veränderte Rahmenbedingungen (zumindest teilweise) selbstständig anpassen zu können. Experte C regt an, dass die Berechnung des technisch und organisatorisch nutzbaren Energieflexibilitätspotentials und dessen wirtschaftliche Bewertung zudem in einem integrierten Optimierungsschritt erfolgen könnte. Ansonsten bestätigen alle drei Experten die (aus ihrer Sicht) vollständigen funktionalen Anforderungen.

Für weiterführende funktionale Anforderung zum Thema Energiemanagementsysteme wird auf die internationale Norm ISO 50001 und für nicht-funktionale Anforderungen an die vorgestellte Systemarchitektur auf ISO/IEC 25000, z.B. ISO/IEC 25010 (Produktqualität) und ISO/IEC 25012 (Datenqualität) verwiesen. Diese werden im Folgenden aus Platzgründen nicht weiter erläutert.

Ein geeigneter Ausgangspunkt zur Konzeption eines EUS für ein datengetriebenes EFM ist die generische Observer/Controller-Architektur von Richter et al. (2006). Diese wurde im Kontext der Energieinformatik bereits mehrfach angewendet, beispielsweise für Smart Homes (Allerding und Schmeck 2011; Becker et al. 2010) oder für Smart Grids (Mauser et al. 2015). Mauser et al. (2015) entwerfen eine hierarchische Observer/Controller-Architektur für Smart Grids und sehen darin u.a. die Integration organischer Energiemanagementsysteme auf Ebene einzelner IU vor. Diese IU sollen sich durch DSM-Aktivitäten vom reinen Energiekonsumenten hin zum „Prosumer“ entwickeln können, welche das Stromnetz durch Energieflexibilitätsmaßnahmen zusätzlich stabilisieren. Der vorliegende Beitrag knüpft an dieser Idee an, wobei der Fokus auf einer Systemarchitektur für ein datengetriebenes EFM liegt, welches innerhalb einzelner IU verortet ist. Zudem werden Kosten- und Nutzenaspekte aus Sicht einzelner IU analysiert, d.h. ohne Berücksichtigung der übergeordneten Netzebene.

Die in diesem Beitrag vorgestellte Systemarchitektur baut auf der Idee auf, dass ein optimales datengetriebenes EFM unter integrierten Chancen- und Risikoaspekten die Integration wesentlicher Komponenten von Energieversorgung und -verbrauch erfordert, d.h. die

Schaffung einer einheitlichen Daten- und Optimierungsplattform voraussetzt. Eine solche Systemarchitektur ist in Abbildung III.3-1 dargestellt.

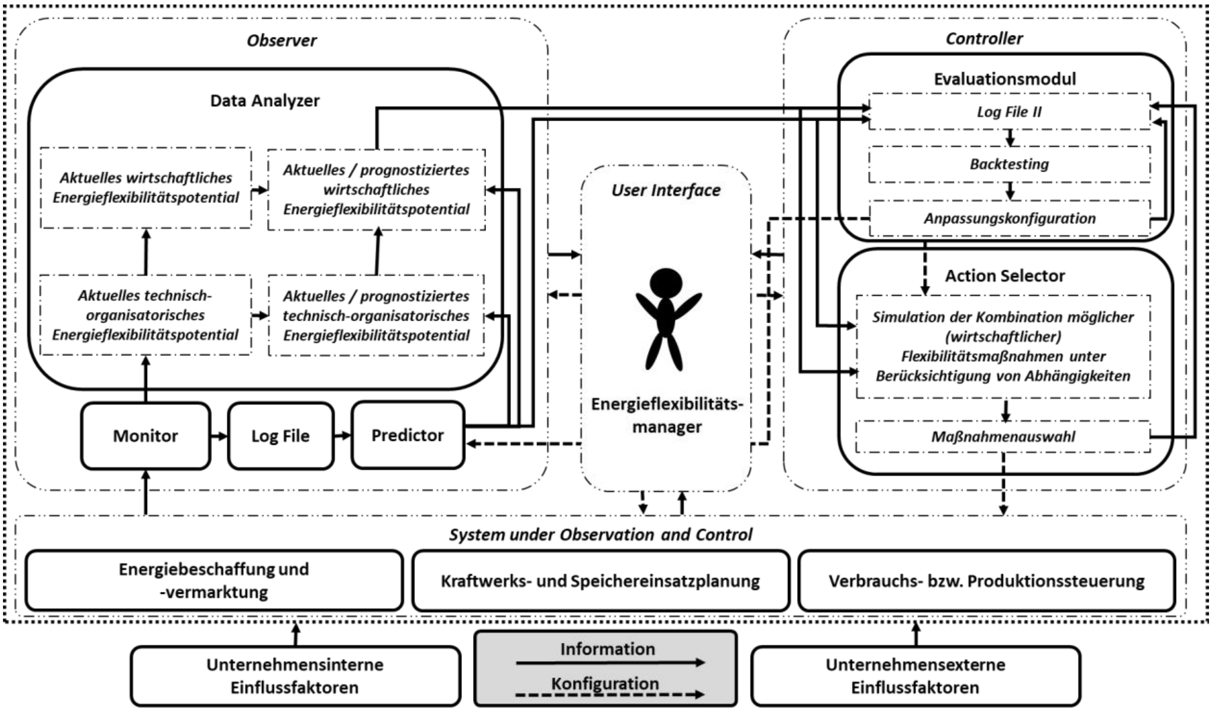

Abbildung III.3-1: Systemarchitektur für ein datengetriebenes EFM

Betrachtungsgegenstand der Observer/Controller-Architektur von Richter et al. (2006) ist das sog. „System under Observation and Control“ (SuOC), welches im Rahmen periodischer Optimierungsiterationen durch einen „**Observer**“ überwacht und einen „**Controller**“ gesteuert wird. Gleichzeitig existieren systemexterne Einflüsse auf das SuOC und die Möglichkeit manueller Nutzereingriffe, wodurch der Zustand des SuOC ständigen Änderungen unterliegen kann. Für den vorliegenden Anwendungskontext entspricht das SuOC allen im IU informationstechnisch integrierten Komponenten von Energieversorgung und -verbrauch. Eine integrierte Betrachtung dieser Komponenten ist sinnvoll, da nur auf diese Weise wesentliche Abhängigkeiten berücksichtigt und das vollständige Optimierungspotential durch das EFM gehoben werden kann. Systemexterne Einflüsse entstehen sowohl aus unternehmensinternen Quellen (z.B. Integration und Desintegration einzelner Komponenten zum EUS, Entwicklung der allgemeinen Auftragslage, Betriebsratsbestimmungen) als auch aus unternehmensexternen Quellen (z.B. energiepolitische Rahmenbedingungen, Marktpreisentwicklungen für Energie, Systemdienstleistungen und Flexibilität, technologischer Fortschritt).

Die Überwachung des SuOC erfolgt über den Observer. Dessen allgemeines Ziel ist die Aggregation bestehender Informationen über das SuOC und deren Übertragung in Kennzahlen, welche den aktuellen Status des SuOC beschreiben und zukünftige Zustände prognostizieren können (Richter et al. 2006). Im Kontext des EFMs erfasst der Observer den Status quo von Energieversorgung und -verbrauch sowie darin enthaltene Abhängigkeiten, berechnet und prognostiziert das Energieflexibilitätspotential, prognostiziert Abhängigkeiten und gibt die gebündelten Informationen als Entscheidungsgrundlage an den Controller weiter. Dabei aggregiert zunächst der „**Monitor**“ (in vorgegebenen Zeitinkrementen) Informationen aller integrierten Komponenten des SuOC, die zur Berechnung des Energieflexibilitätspotentials benötigt werden, sowie Informationen zu den bestehenden Abhängigkeiten zwischen diesen Komponenten. Diese Informationen sind beispielhaft in Tabelle 4 aufgeführt.

Energiebeschaffung und -vermarktung	**Kraftwerks- und Speichereinsatzplanung**	**Verbrauchs- bzw. Produktionssteuerung**
Arbeits- und Leistungspreise für Systemdienstleistungen	Aktueller Kraftwerksfahrplan / Ladestand der Speicher	Aktueller Maschinenfahrplan und zeitliche Randbedingungen
Ausgleichsenergiepreise	Anlagenspezifische Zustandsmenge bzw. mögliche Betriebsweisen	Anlagenspezifische Zustandsmenge bzw. mögliche Betriebsweisen
Gas-, Kohle-, Ölpreise	Nennleistung (Strom / Wärme) Energieerzeuger und -speicher	Nennleistung Produktionsanlagen
Preise für Fernwärme	Leistungsgradient Energieerzeuger und -speicher	Leistungsgradient der Produktionsanlagen
Preise für Strom	Kostenfaktoren der Erzeugung / Aufladung / Entladung	Kostenfaktoren der Produktion / Wertschöpfung
Verträge / Kontingente	Wetterprognosen für PV- und Windkraftanlagen	Lagerbestände vor und nach flexiblen Maschinen
Abhängigkeiten zwischen Komponenten aus Energieversorgung und -verbrauch		

Tabelle III.3-4: Beispielhafte Inputinformationen für ein datengetriebenes EFM

Der Monitor erfüllt damit die funktionale Anforderung „Erfassung Status quo Energieversorgung und -verbrauch sowie deren Abhängigkeiten“. Alle Inputinformationen werden an das „**Log File**“ übergeben, welches die funktionale Anforderung „Speicherung von

Informationen“ adressiert. Zudem werden bestimmte Informationen direkt an den „**Data Analyzer**“ übergeben. Dieser hat zum Ziel, basierend auf den Inputinformationen zunächst das aktuelle technisch-organisatorische Energieflexibilitätspotential und damit das wirtschaftliche Energieflexibilitätspotential zu berechnen (in einem integrierten Schritt, wie von Experte C vorgeschlagen). Zur Berechnung des technisch-organisatorischen Energieflexibilitätspotentials sollten mögliche Energieflexibilitätsmaßnahmen auf Anlagen- bzw. Maschinenebene beschrieben werden. Tabelle III.3-5 zeigt Schlüsselinformationen, auf deren Basis diese Beschreibung erfolgen könnte (angelehnt an Schellmann 2012).

Kennzahl	**Bedeutung**
Aktivierungsdauer	Anlagenspezifische Dauer von der Einleitung einer Energieflexibilitätsmaßnahme bis zu deren tatsächlicher Nutzung
Ablaufdauer	Anlagenspezifische Dauer von der Abschaltung eine Energieflexibilitätsmaßnahme bis zur Rückkehr in den ursprünglichen Planzustand
Leistungsflexibilität	Maximal mögliche anlagenspezifische Leistungssteigerung und -reduktion (ausgehend von einem ursprünglichen Planzustand) im Zuge einer Energieflexibilitätsmaßnahme
Nutzungsdauer	Anlagenspezifische (maximale/minimale) Nutzungsdauer einer Energieflexibilitätsmaßnahme unter technisch-organisatorischen Rahmenbedingungen
Regenerationsdauer	Anlagenspezifischer Zeitpuffer zwischen zwei Energieflexibilitätsmaßnahmen zur „Regeneration“ des technisch-organisatorischen Energieflexibilitätspotentials

Tabelle III.3-5: Schlüsselinformationen zur Beschreibung möglicher Energieflexibilitätsmaßnahmen auf Anlagenebene

Vereinfacht ergibt das Produkt aus Leistungsflexibilität (kW) und Nutzungsdauer (h) die Kapazität des technisch-organisatorischen Energieflexibilitätspotentials (kWh) einer Energieflexibilitätsmaßnahme für einen bestimmten Zeitraum (=Aktivierungsdauer+Nutzungsdauer+Ablaufdauer+Regenerationsdauer). Die Summe über die entsprechenden Energieflexibilitätsmaßnahmen ergibt das gesamte (zur Verfügung stehende) technisch-organisatorische Energieflexibilitätspotential (kWh). Für jede einzelne Energieflexibilitätsmaßnahme sollte im nächsten Schritt eine Wirtschaftlichkeitsanalyse durchgeführt werden, bei welcher anlagenspezifisch Kosten- und Nutzenfaktoren gegenübergestellt werden, die durch Bereitstellung von Energieflexibilität über die entsprechende Nutzungsdauer entstehen. Tabelle III.3-6 führt Kosten- und Nutzenfaktoren beispielhaft auf.

<table>
<tr><th>Kostenfaktoren für Energieflexibilitätsmaßnahme</th><th>Nutzenfaktoren für Energieflexibilitätsmaßnahme</th></tr>
<tr><td>Zusatzkosten für Lastspitzenüberschreitung</td><td rowspan="2">Arbeitspreis für Systemdienstleistungen</td></tr>
<tr><td>Zusatzkosten in vor- und nachgelagerten Prozessen</td></tr>
<tr><td>Zusätzliche Energieversorgungskosten</td><td rowspan="2">Leistungspreis für Systemdienstleistungen</td></tr>
<tr><td>Zusätzliche Lagerkosten und Kapitalbindung</td></tr>
<tr><td>Zusätzliche Personalkosten</td><td rowspan="2">Reduzierte Energieversorgungskosten (z.B. durch Vermeidung von Preisspitzen am Energiemarkt)</td></tr>
<tr><td>Zusätzliche Planungs- bzw. Vorbereitungskosten</td></tr>
<tr><td>Zusätzlicher Ausschuss in Produktionsprozessen</td><td rowspan="2">Vergütung durch Flexibilitätsnachfrager (z.B. auf speziellen Flexibilitätsmärkten)</td></tr>
<tr><td>Zusätzlicher Verschleiß der Anlagen</td></tr>
</table>

Tabelle III.3-6: Beispielhafte Kosten- und Nutzenfaktoren von Energieflexibilitätsmaßnahmen

Der Teil des technisch-organisatorischen Energieflexibilitätspotentials, bei welchem die Nutzenfaktoren die Kostenfaktoren übersteigen, ergibt das wirtschaftliche Energieflexibilitätspotential. Damit erfüllt der Data Analyzer die beiden funktionalen Anforderungen „Berechnung des technisch-organisatorischen Energieflexibilitätspotentials" und „Berechnung des wirtschaftlichen Energieflexibilitätspotentials". Die im Log File gesammelten Inputinformationen dienen nicht nur der Datenspeicherung aus Dokumentationsgründen, sondern werden überdies (im Rahmen jeder Optimierungsiteration) an den „**Predictor**" übergeben. Dieser hat zum Ziel, die vom Monitor gesammelten (aktuellen) Inputinformationen in eine Zukunftsprognose zu überführen. Zur Komplexitätsreduktion bieten sich hierbei Zeitreihenmodelle an, die lediglich basierend auf Vergangenheitswerten eines Inputfaktors Abschätzungen über dessen Zukunftswerte treffen. Für besonders wichtige Inputfaktoren (z.B. Spotmarktpreise für Strom) könnten überdies kompliziertere Regressionsmodelle hinterlegt werden, die neben der eigenen Zeitreihe mehrere Einflussgrößen bei der Prognose eines Faktors berücksichtigen (z.B. Wetterdaten bzgl. Strompreisen). Alternativ können Prognosedaten auch extern beschafft werden. Des Weiteren sollte sämtlichen Prognosen eine Risikoklassifizierung zugewiesen werden, welche

Auskunft über die erwartete Prognosegüte gibt. Diese Risikoklassifizierung kann automatisiert durch den Controller oder manuell durch den Nutzer spezifiziert werden. Die vom Predictor erzeugten Prognosen lassen sich in drei Kategorien unterteilen:

1. Prognosen für Zustände und (auftragsabhängige) Einsatzplanung von Anlagen bzw. Maschinen
2. Prognosen für Kosten- und monetäre Nutzenfaktoren der Energieflexibilität (vgl. Tabelle III.3-6)
3. Prognosen für die (funktionalen) Abhängigkeiten zwischen den einzelnen Komponenten des SuOC

Prognosen der ersten beiden Kategorien überstellt der Predictor an den Data Analyzer. Letzterer kann damit zum bereits berechneten, aktuellen (technisch-organisatorischen sowie wirtschaftlichen) Energieflexibilitätspotential auch die dazu gehörigen Prognosen für einen bestimmten Zeitraum erstellen. Damit erfüllt der Data Analyzer zusätzlich die funktionale Anforderung „Flexibilitätsprognose". Aktuelle und prognostizierte Abhängigkeiten zwischen Komponenten aus Energieversorgung und -verbrauch werden, zusammen mit den berechneten aktuellen und prognostizierten Energieflexibilitätspotentialen, an den Controller weitergegeben.

Der Controller hat allgemein zur Aufgabe, das SuOC mit Steuerungsmaßnahmen unter den vom Nutzer gesetzten Zielen und Rahmenbedingungen so zu beeinflussen, dass ein gewünschtes Verhalten des Systems eintritt und unerwünschtes Verhalten zeitnah unterbunden wird (Richter et al. 2006). Im vorliegenden Anwendungskontext werden die vom Observer überstellten Informationen im ersten Schritt in das „**Evaluationsmodul**" übertragen. Dessen Aufgabe ist es, dem EUS die Fähigkeit maschinellen Lernens zu geben und damit (auch zur Laufzeit) eine kontinuierliche Anpassung des Systems an sich verändernde Umweltzustände zu ermöglichen. Dazu werden die berechnete Energieflexibilität und Abhängigkeiten zunächst in ein weiteres (in diesem Modul integriertes) Log File (II) übertragen. Dieses sammelt (neben den Informationen des Observers) zusätzlich Informationen zu bisherigen Konfigurationsänderungen durch das Evaluationsmodul sowie durch den Controller eingeleitete Energieflexibilitätsmaßnahmen. Mithilfe dieser Informationen wird anschließend das Backtesting des bisherigen EFMs durchgeführt. Dabei können verschiedene Untersuchungen durchgeführt werden, z.B. in welchem Umfang die (in einer früheren Optimierungsiteration) prognostizierten Energieflexibilitätspotentiale und Abhängigkeiten zwischen Komponenten von Energieversorgung und -verbrauch tatsächlich der Realität entsprochen haben und ob die zuvor getroffenen Entscheidungen zur Nutzung des wirtschaftlichen Energieflexibilitätspotentials tatsächlich die prognostizierten Energiekosteneinsparungen (bzw. Erlöse aus der Flexibilitätsvermarktung) erzielen konnten. Durch einen Soll-Ist-Vergleich bewertet das Backtesting demnach die Güte der Prognosen für Energieflexibilitätspotentiale, Abhängigkeiten und die Auswahl konkreter Energieflexibilitätsmaßnahmen. Anschließend kann das Evaluationsmodul Anpassungskonfigurationen an Predictor und Action Selector vornehmen. Hierbei können unterschiedliche Methoden des maschinellen Lernens verwendet werden (z.B. künstlich neuronale Netze, evolutionäre Algorithmen), welche zum Ziel haben, die Prognosegüte zu verbessern. Das Evaluationsmodul adressiert damit die funktionalen Anforderungen „Speicherung von Informationen" und „Backtesting- bzw. Lernfähigkeit". Im zweiten Schritt werden die vom Observer überstellten Informationen an den „**Action Selector**" übertragen. Ziel dieses Moduls ist die Einleitung von geeigneten Steuerungsmaßnahmen (Handlungsempfehlungen) zur Nutzung vorhandener Energieflexibilität. Das wirtschaftliche Energieflexibilitätspotential wird dabei auf Anlagen- bzw. Maschinenebene betrachtet, wobei das System versucht, mittels Simulationsverfahren die bestmögliche Kombination von Energieflexibilitätsmaßnahmen zu ermitteln. Im Gegensatz zum Data Analyzer, welcher einzelne Energieflexibilitätsmaßnahmen im Rahmen einer isolierten Betrachtung bewertet, werden im Action Selector bestehende Abhängigkeiten zwischen unterschiedlichen Energieflexibilitätsmaßnahmen berücksichtigt. Insbesondere wird analysiert, welche Auswirkung bzw. Probleme durch die Kombination mehrerer Energieflexibilitätsmaßnahmen erzeugt werden. Hierfür ist es wichtig zu beachten, dass die Abhängigkeiten zwischen einzelnen Anlagen bzw. Maschinen und der damit verbundenen Prozesse als Inputinformationen dem System vorliegen und als Restriktionen in die Optimierung mitaufgenommen werden müssen. Sind beispielsweise mehrere durch das EFM erfasste Anlagen konsekutiv in einer Wertschöpfungskette angeordnet, so kann sich die Mehr- bzw. Minderproduktion einer Anlage auf das Flexibilitätspotential der vor- und nachgelagerten Anlagen auswirken, abhängig von Pufferkapazitäten und den Fähigkeiten der vor- und nachgelagerten Anlagen, den Mehr- bzw. Minderverbrauch an Rohstoffen bzw. Halbfabrikaten zu kompensieren. Ähnliches gilt, wenn die Anlagen parallel am selben Wertschöpfungsschritt arbeiten. Die Nutzung von Energieflexibilität einer Anlage kann dann die Energieflexibilität der anderen Anlagen ebenfalls aufbrauchen. Insbesondere können Abhängigkeiten bei der Regenerationsdauer der Energieflexibilität existieren. Weitere wichtige Abhängigkeiten können u.a. in Bezug auf inhärente Abhängigkeiten zwischen Anlagen (z.B. Hilfsaggregate für eine oder mehrere Maschinen), das Lastspitzenmanagement (Lastspitzenglättung zur Vermeidung von Netzentgelten) und Umweltvorschriften (Emissionsgrenzwerte) entstehen. Über die Einbeziehung von Prognosedaten kann zudem analysiert werden, ob verfügbare Energieflexibilitätspotentiale sofort oder zu einem späteren Zeitpunkt genutzt werden sollen. Basierend auf den Simulationsergebnissen wählt der Action Selector die (im Erwartungswert) wirtschaftlichste Kombination von Energieflexibilitätsmaßnahmen aus. Der Zeithorizont, auf den sich diese (angedachten) Flexibilitätsmaßnahmen erstrecken, hängt von der Konfiguration des EUS bzw. von den zur Verfügung gestellten Inputinformationen ab. Abhängig vom Wunsch der Anwender kann das System die gewählten Flexibilitätsmaßnahmen entweder direkt in Steuerungssignale an die entsprechenden Komponenten von Energieversorgung und -verbrauch umwandeln oder lediglich Handlungsempfehlungen erstellen, die manuell von Befugten freigegeben werden müssen. Der Action Selector erfüllt damit insbesondere die funktionalen Anforderungen „Steuerung von Energieversorgung und -verbrauch“ und „wirtschaftliche Optimierung“. Der beschriebene Kreislauf sollte sich in definierten Zeiteinheiten wiederholen. Dabei gilt, dass eine höher frequentierte Optimierung die Steuerungsqualität des Systems erhöhen kann, gleichzeitig jedoch rechenintensiver ist und mehr Interaktion mit dem Nutzer verlangt. Für eine niedriger frequentierte Optimierung gilt das Gegenteil.

Menschliche Ziele und Rahmenbedingungen werden durch ein **„User-Interface“** erfasst, welches einerseits zur Übertragung menschlicher Inputinformationen an das System dient und andererseits wesentliche Systemparameter dem Menschen als Outputinformationen ausgeben bzw. visualisieren kann. Beispielhafte In- und Outputinformationen im Kontext eines datengetriebenen EFM sind in Tabelle III.3-7 aufgeführt.

Inputinformationen	**Outputinformationen**
Anpassung technologischer Restriktionen für die Optimierung (z.B. zulässige Laststufen und Lastgradienten einzelner Maschinen, bevorzugte Nutzung von Erzeugern/Speichern/Verbrauchern)	Erfolgskennzahlen, die dem Nutzer Auskunft darüber geben, welche Energieflexibilitätsmaßnahme bislang zu welchen Kosteneinsparungen bzw. Erlösen geführt hat
Anpassung wirtschaftlicher Restriktionen für die Optimierung (z.B. Voraussetzung einer erwarteten Mindesteinsparung, Vermarktung von Flexibilität auf vordefinierten Märkten, Berücksichtigung von Risikopräferenzen)	Logfile aller menschlichen (manuellen) Eingriffe in das datengetriebene EFM
Einstellung der Darstellung/Visualisierung von Informationen für den Nutzer	Logfile automatisch erzeugter Systemkonfiguration und Steuerungsmaßnahmen (Handlungsempfehlungen) zur Nutzung von Energieflexibilität
Manuelle Aktivierung / Deaktivierung des EUS bzw. einzelner Funktionalitäten	Technologische und wirtschaftliche Restriktionen, die das EUS aktuell bei der Optimierung berücksichtigt

Tabelle III.3-7: Beispielhafte In- bzw. Outputinformationen von bzw. für menschliche Anwender im EFM

Einstellungen über das User-Interface werden zur Laufzeit an die entsprechenden Systemkomponenten weitergegeben. Das User-Interface adressiert damit die verbleibende gleichnamige funktionale Anforderung.

III.3.5 Handlungsempfehlungen

Das Ergebnis wurde mit den drei Experten auf dessen Praxistauglichkeit hin überprüft. Experte A sieht den besonderen Mehrwert eines datengetriebenen EFMs v.a. in zwei Punkten: Zum einen fehlen bislang übergreifende Informationssysteme, welche Subsysteme der Energieversorgung und des -verbrauchs vernetzen und somit einen gemeinsamen Datenaustausch bzw. eine gemeinsame Optimierung ermöglichen. Zum anderen fehlt die Fähigkeit zur Prognose zahlreicher (v.a. wirtschaftlicher) Parameter. Er betont allerdings die Notwendigkeit, dass bei der Implementierung eines solchen Systems eine besondere Berücksichtigung des zeitlichen Planungshorizonts stattfindet, da eine Energieflexibilitätsplanung für wenige Minuten bis Stunden im Gegensatz zu mehreren Wochen bis Monaten fundamental andere Parameter, Ziele, Rahmenbedingungen und Steuerungsmaßnahmen (Handlungsempfehlungen) aufweisen kann. Zudem sollten nicht nur rein organische oder konventionelle EUS, sondern auch „Hybridsysteme“ angedacht werden, welche die Ausführung von Energieflexibilitätsmaßnahmen teilweise automatisiert und teilweise (bei kritischen Eingriffen) manuell ermöglichen. Experte B unterstützt diese Aussage dahingehend, dass die Ausführung von Energieflexibilitätsmaßnahmen in der Praxis häufig manuell durch Maschinenverantwortliche geschieht. Er empfiehlt, dass die Prognose- und Simulationsfähigkeit des Systems nicht nur im Zuge der (automatisierten) Optimierungsiterationen, sondern auch zur manuellen Risikobewertung („Spielwiese“) für Nutzer einsetzbar sein sollte. Damit könnten letztere deren Rahmenvorgaben an das System erproben und konkretisieren. Experte C betont, dass in der energiewirtschaftlichen Praxis bereits ähnliche Lösungen im Einsatz sind. Diese werden jedoch vorwiegend zur Energiebeschaffung und Kraftwerkseinsatzplanung eingesetzt und greifen daher kürzer als der hier dargestellte Ansatz. Zukünftige Lösungen sollten bzw. müssen (auch aus regulatorischer Sicht) insbesondere eine verbesserte Integration von Energieverbrauchern, eine verbesserte Nutzerinteraktion und automatisiertes Handeln ermöglichen. Ein datengetriebenes EFM sei dabei der richtige Weg und voraussichtlich v.a. für IU mit größerem Energieverbrauch interessant, wobei die Wirtschaftlichkeit solcher Systeme individuell zu prüfen ist.

Des Weiteren werden zusätzliche Handlungsempfehlungen gegeben, die insbesondere für die erstmalige Nutzung von Energieflexibilität nützlich und somit vorbereitend für den vorgestellten Ansatz dieses Beitrags sind:

Im *ersten Schritt* sollten Unternehmen das vorhandene Energieflexibilitätspotential bzw. die dazugehörigen Verbrauchs- und Erzeugungsanlagen analysieren. Für Energieflexibilitätsmaßnahmen eigenen sich auf Verbraucherseite v.a. hochfrequentierte und verschieb- bzw. unterbrechbare („Batch-“) Prozesse bzw. energieintensive Anlagen mit vorhandenen Überkapazitäten. Anlagen, die dagegen hohe Stillstandzeiten aufweisen oder durchgehend auf (nahezu) Volllast betrieben werden, besitzen kaum Energieflexibilitätspotential. Auf Erzeugerseite sind Anlagen geeignet, welche mit möglichst geringem Zeitaufwand, Verschleiß, Schadstoffausstoß und Mehrverbrauch, idealerweise mehrmals am Tag, hoch- bzw. heruntergefahren werden können (z.B. Gasmotoren).

Im *zweiten Schritt* sollten Vermarktungsmöglichkeiten der vorhandenen Energieflexibilität untersucht werden. In Kapitel III.3.3 wurde dazu vor allem auf Energy-Only-Märkte und Märkte für Systemdienstleistungen verwiesen. Große und energieintensive Unternehmen verfügen teilweise über einen eigenen Bilanzkreis und können ihre vorhandene

Energieflexibilität auf den genannten Märkten selbstständig vermarkten. Alle anderen Unternehmen erfüllen häufig jedoch nicht die jeweils geforderten Kriterien für eine selbstständige Marktteilnahme. Diese Unternehmen sollten daher die Angebote von Aggregatoren prüfen, d.h. von Energieversorgungsunternehmen oder unabhängigen Dritten, welche die Energieflexibilität mehrerer Anbieter bündeln und damit den geforderten Mindestkriterien entsprechen (VKU 2015). Beispielsweise bietet die Next Kraftwerke GmbH flexible Stromtarife, deren Preisverlauf bis zu viertelstundengenau den Spotpreisen an der EPEX Spot entspricht, dazugehörige Preisprognosen sowie die Teilnahme der Unternehmen an unterschiedlichen Regelleistungsmärkten durch Aggregation von mehreren unternehmensinternen und -externen Energieerzeugern (virtuelles Kraftwerk) und Energieverbrauchern.

Im *dritten Schritt* sollten interne Vorbereitungen für die operative Durchführung eines EFMs getroffen werden. Nach Klärung der Zuständigkeiten sollte eine einheitliche Datengrundlage zu den Verbrauchs- und Erzeugungsanlagen geschaffen werden, indem wesentliche Betriebsparameter regelmäßig und automatisiert abgerufen und in einer zentralen Datenbank abgespeichert werden. Dazu ist es notwendig, Verbrauchs- und Erzeugungsanlagen, falls noch nicht geschehen, mit intelligenten Messsystemen auszustatten. Diese Datenbank sollte dann um Marktdaten angereichert werden, welche für die angedachte Vermarktung der Energieflexibilität relevant sind. Anschließend sollten aus den vorhandenen Energieflexibilitätspotentialen einzelne Flexibilitätsmaßnahmen auf Anlagen- bzw. Maschinenebene beschrieben (vgl. Tabelle III.3-5) und in einem Kalkulationsprogramm (z.B. Microsoft Excel) hinterlegt werden. Dann sollten jeder Flexibilitätsmaßnahme Kostenfaktoren gemäß Tabelle III.3-6 zugewiesen werden. Zusätzlich sollte eine Logik hinterlegt werden, die Aufschluss darüber gibt, ob einzelne Flexibilitätsmaßnahmen in Kombination miteinander durchführbar sind oder nicht. Eine erste Möglichkeit zur optimierten Steuerung der Flexibilitätsmaßnahmen kann mittels eines einfachen linearen Optimierungsproblems geschaffen werden, welches sich beispielsweise durch das Simplex-Verfahren lösen lässt. Damit könnte ein EFM erstmalig operativ ausgeübt werden.

Im *vierten Schritt* gilt es, die theoretisch optimierte Nutzung von Energieflexibilität praktisch umzusetzen. Innerhalb von IU kann das EFM auf Widerstände der Mitarbeiter stoßen. Insbesondere Maschinenverantwortliche streben bis heute häufig nach einem Effizienzoptimum der Fahr- bzw. Betriebsweise ihrer Anlagen. Die Nutzung von

Energieflexibilität kann dabei einen Zielkonflikt erzeugen, da unter Berücksichtigung von Marktinformationen die wirtschaftlich optimale Nutzung dieser Anlagen nicht zwangsläufig der technologisch optimalen Nutzung entsprechen muss. Beispielsweise könnte ein höherer Anlagenverschleiß und Mehrausschuss in Produktionsprozessen durch Energieflexibilitätsmaßnamen zu Effizienzverlusten führen, obwohl diese durch einen kostengünstigeren Energieeinkauf aus ökonomischer Sicht sinnvoll sind. Es ist somit eine integrierte Betrachtung von Effizienz und Flexibilität im Energiemanagement bzw. die Ermittlung einer optimalen „Flex-Efficiency" (Ecofys 2016) und eine darauf aufgebaute Kommunikation erforderlich. Im Zuge dessen sollten ggf. vorhandene Anreizsysteme in der Produktion angepasst werden (z.B. durch Abkehr von rein effizienzbezogener Erfolgsmessung). Insbesondere sollten wesentliche Stakeholder, die über alle Hierarchieebenen eines IU zu suchen sind, in die Implementierung des EFMs (konstruktiv) miteingebunden werden. Diesen sollte anhand plakativer Business-Case-Rechnungen klar aufgezeigt werden, weshalb sich die Nutzung von Energieflexibilitätspotentialen für die Gesamtunternehmung lohnt.

Im *fünften Schritt* sollte noch zukunftsgerichtet analysiert werden, ob vorhandene Energieflexibilitätspotentiale durch sinnvolle Investitionen gesteigert werden können. Typische Beispiele sind die Ermöglichung eines Teillastbetriebs durch feinstufigere Anlagensteuerung, der Ausbau von Produktions- und Lagerkapazitäten zur Generierung flexibler Überkapazitäten und die Anschaffung einer flexiblen Anlage zur Energieeigenerzeugung (z.B. Blockheizkraftwerk mit Gasmotoren). Während die Speicherung elektrischer Energie innerhalb hergestellter Produkte durch einen energetischen Wirkungsgrad von 100 % besonders sinnvoll sein kann, eigenen sich KWK-Anlagen durch einen Wirkungsgrad von 80% und zusätzlicher Förderung durch das KWK-Gesetz (Simon 2017). Energieflexibilitätsmaßnahmen besitzen einen Optionswert, da diese durchgeführt werden können, aber nicht durchgeführt werden müssen (Fridgen et al. 2016). Dieser Optionswert sollte bei Investitionsentscheidungen miteinbezogen werden. Dabei sollte auch berücksichtigt werden, dass durch die gesellschaftlichen Ausbauziele von Photovoltaik- und Windkraftanlagen, den geplanten Atomausstieg bis 2022 und den angestrebten Rückbau von Kohlekraftwerken (im Hinblick auf die CO_2-Ziele) die Volatilitäten auf Energiemärkten zukünftig erwartungsgemäß steigen sollten und damit auch der Wert von Energieflexibilitätsmaßnahmen.

III.3.6 Danksagung

Der Autor bedankt sich herzlich beim Bundesministerium für Bildung und Forschung (BMBF) für die finanzielle Unterstützung und beim Projektträger Jülich (PtJ) für die Betreuung des Kopernikus-Projektes „SynErgie“.

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III.4 Research Paper 7: "The Regional and Social Impact of Energy Flexible Factories"

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Published in:	Procedia Manufacturing, 21, 468-475

Abstract:

The change of electricity supply from conventional to renewable energy sources is a challenge for the whole society. This transition causes an increase of volatility in electricity supply and therefore threatens both, grid stability and, also, electricity price stability. Besides cost-intensive countermeasures such as grid expansions and power-to-X storage technology, the incentivized change in electricity use (energy demand flexibility) is a promising approach. Today, when it comes to production matters, energy is considered as a resource which is immediately available on demand. In contrast, future scenarios draw a picture, in which

electric energy will become a resource that requires planning and control. Energy flexible factories will be an important part of our society with an important ecological and social impact. The paper presents a transdisciplinary approach to shape a sustainable electricity supply in the discourse with regional stakeholders from a technical, ecological and social background.

III.4.1 Introduction

Global greenhouse gas emissions continue to grow. In 2015, participants of the UN Climate Change Conference in Paris agreed to pursue efforts to limit the temperature increase to 1.5 degrees Celsius above pre-industrial levels [1]. Germany, one of the top five countries in renewable power generation [2], has claimed to take a worldwide lead in climate protection [3]. In 2016, renewable energies already reached 31 % of the German electricity mix [4]. The expansion target for renewable energies, imposed by the Germany federal government, amounts 80 % up to the year 2050 [5]. This ambitious project will enable a gradual withdrawal from Germany's nuclear energy programme by 2022 and to reduce its greenhouse gas emissions by 80 to 95 % until 2050 compared to 1990 [4]. The change in German energy policy, that is called *energy transition,* addresses complex interrelations between heterogeneous actors from the technical, political, legal and societal sector.

One of the biggest challenges for the energy transition is the intermittent nature of photovoltaic and wind power systems, which constitute the largest share within the German renewable electricity generation [5]. Uncontrollability and difficult predictability of solar radiation and wind conditions threaten the balance between electricity supply production and demand. Consequently the grid stability in central Europe is challenged. Besides cost-intensive solutions of grid expansions and power-to-X storage technology, demand side management (DSM) is a promising approach for utilizing flexibility in electricity demand to balance fluctuating energy availability [6]. Thereby, DSM was originally defined as "the planning and implementation and monitoring of […] activities designed to influence customer use of electricity in ways that will produce desired changes in the […] load shape, i.e., changes in the time pattern and magnitude of […] load" [7]. Palensky and Dietrich [6] divide DSM further into Energy Efficiency, Time of Use, Demand Response (DR) and Spinning Reserve. For purpose of simplification, we summarize Time of Use and Demand Response by the term *energy flexibility*, describing the ability of a manufacturing company to adapt the production to short-term changes in electrical energy provision with least possible loss in time, effort, costs and performance [8,9]. It induces changes in electricity demand through incentives such as varying electricity prices that are an important measure to encounter fluctuating energy availability [10]. Especially the industrial sector, which is by far the largest electricity consumer with a share of 47 % of the total German net electricity consumption in 2016 [11] has a high potential for energy flexibility. Although there are some companies in the industrial sector that already participate in energy flexibility markets, e.g. balancing power markets, most of the capability of energy flexibility remains unused. Recent studies assess the potential of DSM in German industries between 1.8 and 15 GW [12,13].

Apart from monetary incentives and technological enablers to leverage this potential, ecological and social aspects of energy flexibility have to be considered in order to achieve a broad public acceptance. For this reason a subproject of the project *SynErgie*, funded by the German Federal Ministry of Education and Research (BMBF), aims for prototyping a new form of cooperation between society and the energy flexible factory with transdisciplinary research (TR) and design thinking. “TR deals with problem fields in such a way that it can grasp the complexity of problems, take into account the diversity of life-world and scientific perceptions of problems, link abstract and case-specific knowledge and develop knowledge and practices that promote what is perceived to be the common good” [14].

SynErgie has the objective to conceptualize, develop and implement a digital market platform for the trading of energy flexibility within the industrial sector. This is why the project team pursues a bottom-up-approach by taking one region into a closer examination and transferring the results to other regions. In the context of the SynErgie project, the aim of the so-called *energy flexible model region Augsburg* is therefore to take a holistic perspective on energy flexibility in a regional context to uncover the local obstacles for energy flexibility with regard to ecological and social aspects. Thus, a holistic perspective must integrate the impacts on all technological, ecological and social stakeholders and it demands for a collaboration of those stakeholders from different disciplines and backgrounds. Stakeholders like scientists, plant operators, plant employees or conservationists must perform a transdisciplinary discussion process to uncover and assess different problem areas that emerge from a regional integration of energy flexibility. This offers a basis to develop appropriate measures that utilize and increase energy flexibility and to transfer the knowledge gained into other regions and therefore on a national level. In order to contribute to the transdisciplinary efforts of SynErgie and the energy flexible model region Augsburg, the authors aim for working on the following research objective:

Designing and illustrating a transdisciplinary approach to utilize (industrial) energy flexibility with respect to technological, ecological and social restrictions.

The paper presents the transdisciplinary dialog process in the energy flexible model region Augsburg, which is also a guideline for regional and national efforts within the SynErgie project. Thus, in Section III.4.2, Augsburg as energy-flexible model region is introduced in detail. In Section III.4.3, impacts of energy flexible factories within the transdisciplinary dimensions technosphere, soziosphere and ecosphere are illustrated. Section III.4.4 gives an overview of the transdisciplinary approach and the methodology. Section III.4.5 presents the research project's progress and intermediate results. Section III.4.6 concludes with an outlook.

III.4.2 Introducing the energy-flexible model region Augsburg

The introduction emphasized the importance of a regional approach to balance electricity supply and demand by utilizing and increasing industrial energy flexibility. Therefore, it is necessary to build up a regional platform at distribution grid level to synchronize renewable energies in the region with the energy demand by using them most efficiently. To analyse the impact of energy flexible factories, the region around the German city Augsburg has been chosen as a model region. The following subsections will present key facts of the region and a first overview of energy flexible factories with their social and ecological impacts.

III.4.2.1 The regional structure of Augsburg

Augsburg is a German city with nearly 300.000 inhabitants in the city and 600.000 inhabitants in its surrounding region. Augsburg serves as capital of the district Swabia and is the third largest city of Bavaria. The industrial sector includes small, medium and large companies [15]. The five most important business areas are mechatronics and automation, fiber composite, information technologies, logistics and environment [16]. Therefore, manufacturers of the following sectors are important regional employers: machinery and equipment, rubber and plastic products, chemicals and chemical products, pulp, paper and paper products [17]. From an energetic point of view Bavaria and especially Augsburg offer a heterogeneous mixture of industrial energy consumsers, including energy-intensive companies (see Figure III.4-1). However, many companies are not directly located in the city. Hence, we broaden our scope onto the surrounding region of Augsburg, the so-called *economic region Augsburg*. Thereby, the city of Augsburg is characterized by a high electricity demand and low renewable electricity supply, while the surrounding regions have a low electricity demand and a high capacity of renewable energies, particularly photovoltaics. Within that scope the overall annual electrical energy demand of households and industries is 4.600 GWh, whereby the industry in the economic region Augsburg contributes about 74 % [18].

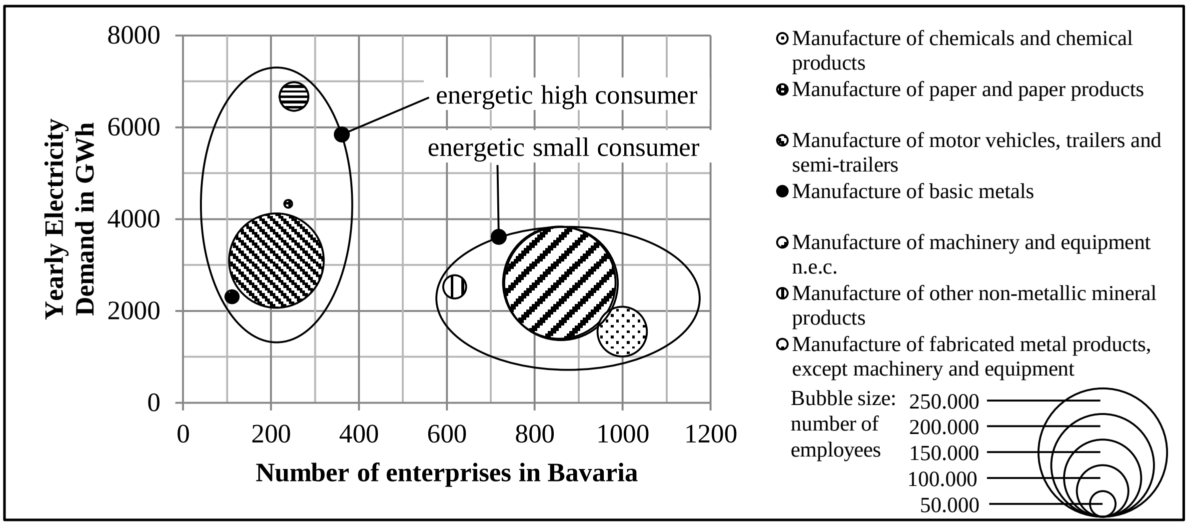

Figure III.4-1: Classification of regional industrial energy consumer [19]

III.4.2.2 Regional change in energy policy

The regional turnaround in energy policy is affected by the Bavarian renewable expansion targets. Therefore the prospective changes are presented in the following subsection. The regional climate protection concept of the economic region Augsburg includes the objective to decrease CO_2 emissions by 55 % until 2030 in comparison to 2009. Measures to reach this ambitious objective include both an increase of energy efficiency and a rising share of renewable energies [20]. In the last years, the installed capacity of renewable energies in Bavaria has been extended from 5 GW up to 15 GW, which nowadays represent 50 % of the power genation portfolio. Accordingly, 40 % of the electrical energy supply in Bavaria is provided by renewable energies. The remainig part is covered by 43 % from nuclear and by 17 % from fossil power plants (see Figure III.4-2). As stated in the introduction, the existing nuclear power plants will be successively turned off until 2022.

As the nuclear power plant in Gundremmingen ,which is located close to Augsburg will be shut down until 2022, there will be a local gap in electricity supply. In short-term, this gap cannot be covered by transporting wind power from the north of Germany or pump storaged power from Austria, as transmission grid capacity is limited. In addition, conventional electricity supply from France and Czech Republic may become limited in terms of time and volume. For this reason, regional energy sources have to be used in a most effective way to guarantee the security of supply, by taking into account that the supply volatility in the distribution grid level will increase through the use and the expansion of renewable energies. In order to incentivize the industries to offer energy flexibility and to enable a prioritization of local balancing measures, the current power market design needs to be challenged.

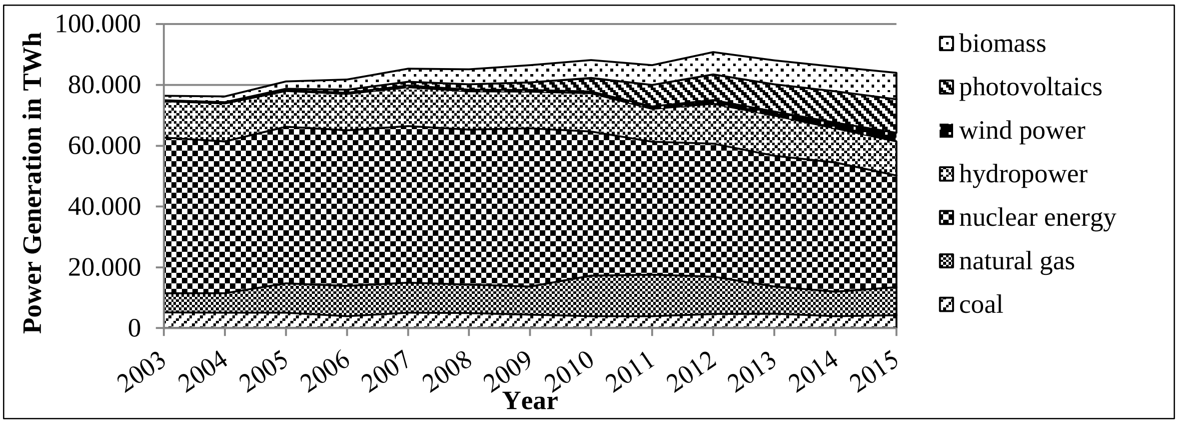

Figure III.4-2: Mixture of the energy supply in Bavaria (2003-2015) [19]

III.4.3 Impact of energy flexible factories

Due to their large impact on Augsburg's energy demand, energy flexible factories may significantly contribute to grid stability[21]. To realize this energy flexibility potential, factories need to be integrated into a smart grid on a regional and a national level. Thereby, manual or automated changes in the load profile can be performed between the grid and production. Thus, energy flexibility in production has the potential to contribute to the power system's stability.

However, as manufacturing companies are individual socio-economic systems in a regional context, technical, social and ecological aspects have to be considered. Therefore, three spheres are defined which integrate the individual interests of the different stakeholders in the context of industrial energy flexibility and support the creation of solutions and guidelines for a successful implementation within the region. This approach is illustrated in Figure III.4-3.

The *technosphere* comprises industrial companies, utility companies and service-companies (e.g. IT) with the objective of formulating and utilizing flexibility measurements throughout the different industries. Second, the *sociosphere* unites labor unions, regional municipality, utility companies and citizen groups as a think tank, which elaborates a local energy transition agenda and its impact to quality of life, work and the energy market situation within the region. Thereby, a municipal statement towards energy transition objectives, the Regional Target Scenario, flexibility measures, which companies in the region may use for energy flexibility (e.g. weekend production) are formulated and discussed. Finally, the *ecosphere* merging interest groups like ecological activists, governmental and non-governmental environment institutions in order to assess the impact of possible energy flexibility measures on the regional environment. All spheres work on their own solutions and guidelines. The three spheres are mutually integrated in a collaborative procedure where preliminary results are shared and combined in common meetings such as decisions for further actions. Using insights of the technological, social and ecological attitude towards energy flexibility, technically realisitc flexibility levels are joined with socio-ecological guidelines. As a result, appropriate energy flexibility measures are identified for each factory that meets the individual requirements of the respective stakeholders. Hence, factories are able to utilize their energy flexibility potential within the region and therefore contribute proactively to the local and national energy transition.

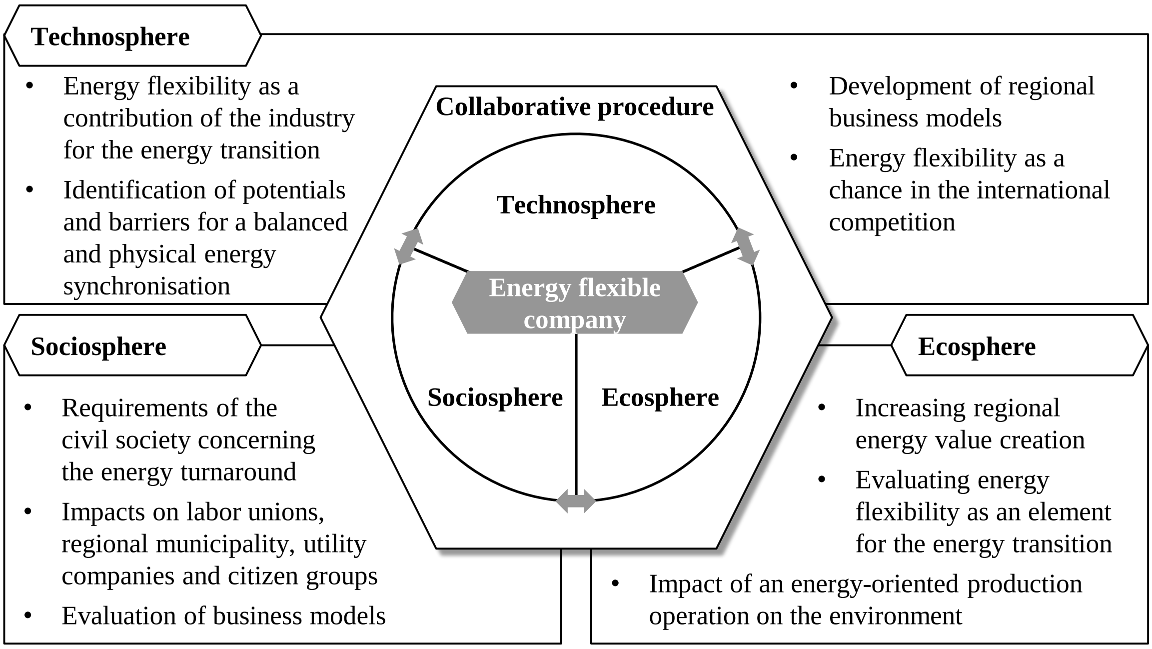

Figure III.4-3: The collaborative procedure and the three spheres of the energy flexible model region

III.4.4 Approach and methodology

As shown, the German energy transition poses many technical and societal challenges. These can be understood and tackled best by a transdisciplinary approach: “Transdisciplinarity is a reflexive research approach that addresses societal problems by means of interdisciplinary collaboration as well as the collaboration between researchers and extra-scientific actors; its aim is to enable mutual learning processes between science and society; integration is the main cognitive challenge of the research process” [22].

The transdisciplinary approach for the energy flexible model region includes the following three phases Co-Design, Co-Production, Co-Communication and Transdisciplinary Re-Integration (see Figure III.4-4). At the Co-Design societal as well as technological problems are discussed within the different research spheres (i.e. the sociosphere, ecosphere and technosphere). The goal is to establish a mutually shared understanding, to frame the problem, and to derive specific research questions. During the phase Co-Production scientific knowledge (like new technologies) and societal knowledge (how to’s, values) are gathered together to produce valuable solutions. Finally, the phase Co-Communication and Transdisciplinary Re-Integration represents a remarkable challenge, integrating the different perspectives in the cluster meetings twice a year. The results of the generated knowledge have to be fed back into the scientific and societal practice. This requires an agora to deliberate and reflect with stakeholders and citizens. The Regional Target Scenario for Augsburg is an important interface which needs to be defined during the research progress. It consists of a shared vision of all partners and citizens for the renewable electricity mix and its flexible use of the industry in the region Augsburg.

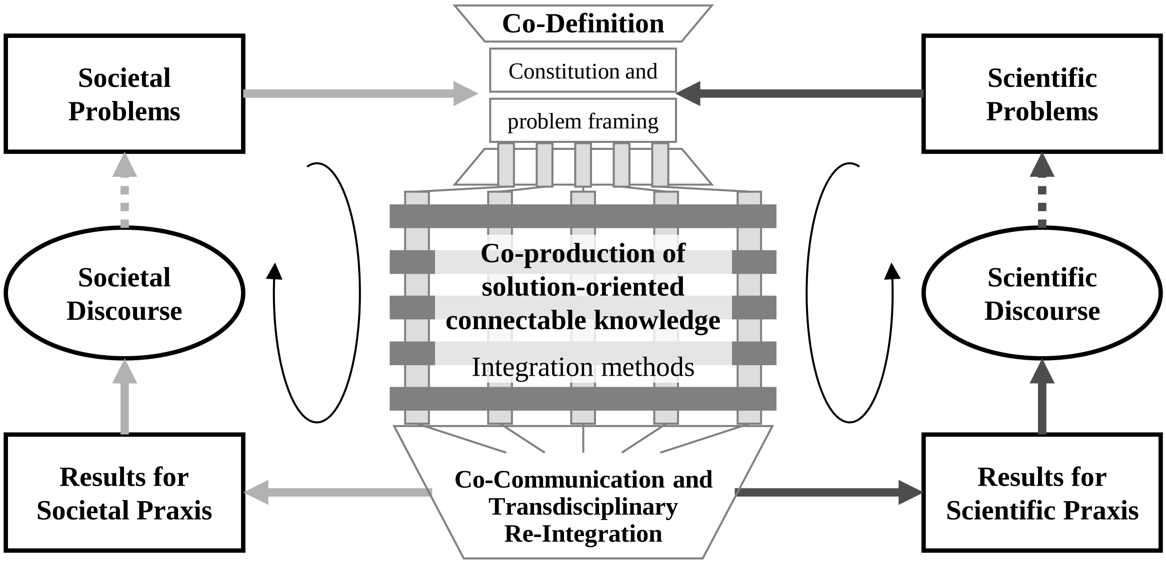

Figure III.4-4: Transdisciplinary Research Approach [23]

Transdisciplinarity means that scientist and practitioners from industry, politics, administration, NGOs and citizens contribute to the research process design and to the implementation of solutions. It is important for the overall participatory process to define roles and responsibilities as well as the decision and feedback architecture. To ensure a high-quality cooperation, the transdisciplinary approach is combined with a human-centred design methodology.

Design is a way of assessing and creating services and products, focusing on their usability, usefulness and engagement to the people creating and using them. This enables to understand, define, develop and evaluate relevant knowledge with stakeholders from different affected sectors. The chosen research design is oriented on the *Double Diamond Model*

[24] which differentiates between two main phases: 1) *Problem Area* and 2) *Solution Area*, with a divergent and convergent phase for each area. The theoretical base builds on successive phases, as illustrated in Figure III.4-5. Solution area is the connection between the Regional Target Scenarios and the factories.

The underlying design principles are implemented by different methods throughout the entire process. The process is based on the principles of transdisciplinary research and are conducted with a human centred design approach. To guarantee valid results that build on one another, the research process is divided into three phases:

Phase 1) Co-Definition: Setting the foundation for cooperation, creating a shared understanding of process and roles, collecting stakeholder demands and worries concerning the energy flexible factory

Co-Define: Defining main challenges and opportunities, summarizing insights in regional target scenario for Augsburg

Phase 2) Co-Production: Developing ideas and prototypes for fields of action and business models within the context of the energy flexible factory

Phase 3) Co-Communication & Transdisciplinary Reintegration: Testing and synthesizing pathways for an energy flexible factory in Augsburg and transfer to other regions

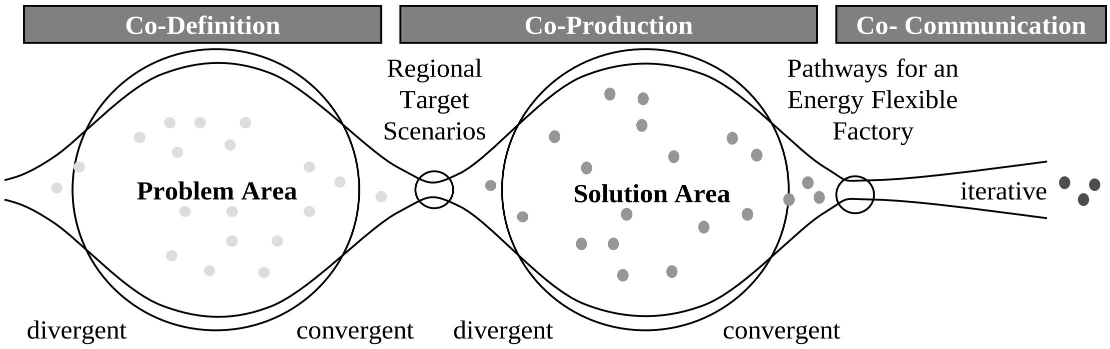

Figure III.4-5: Process design for the energy flexible model region Augsburg (based on [24])

III.4.5 Progress and intermediate results

So far, the phase of Co-Definition has been approached from various angles: Stakeholders have been engaged, Understanding, has been approached, in which the kick-off workshops of the entire cluster and each sphere have been conducted. In order to collect data and knowledge within the four relevant sectors (science, industry, politics and civil society) the regional stakeholders were asked for related topics, challenges and opportunities. Based on these knowledge-maps the four groups have synthesized their needs and interests with regard to the energy flexible factory. For this purpose *Persona Profiles* were used to develop a *Position Map* displaying the parties that will benefit or lose and support or hinder the developments at the moment. First results are the following identified challenges and topics: social innovations, establishment of the economic framework, political support to foster the transition and adoption of the regulatory framework.. Questions regarding the implementation of the research project in companies and markets, the tasks of the research agenda, the achievement of societal acceptance for the project approach as well as the question of fairness in the transition process and the development of new roles and positions in different stakeholder groups were outlined. One question, the stakeholder focus on, is how to cope with the ambiguity between economically viable solutions and affordable costs for all consumers.

The complex process synchronization between the different research spheres (the sociosphere, ecosphere and technosphere) has been specified in order to develop a mutually shared understanding of feedback and co-communication structures throughout the entire process. This transdisciplinary research approach is needed as a basis for co-producing the Regional Target Scenario for Augsburg.

III.4.6 Discussion and outlook

Reflecting the cooperation so far, knowledge integration can be mentioned as the biggest challenge, especially regarding the process facilitation and coordination in transdisciplinary research. The evaluation of the project is outlined by the following three dimensions [23]:

1) Cognitive-epistemic dimension: The differentiation and linkage of disciplinary knowledge bases, as well as practical real-world knowledge is still underdeveloped. This means that the limits of one’s own knowledge have to be clarified and methods and building theories need to be developed and strengthened in the process.

2) Social and organizational dimension: The participating researchers’ interests and activities are going to be more and more transparent and mutually reasonable. All partners are aware of the challenges and willing to learn.

3) Communicative dimension: The different linguistic expressions and communicative practices are perceived. One goal of the project is to develop a common discursive practice in which mutual understanding and communication is possible. This will be a significant step for a mutually shared understanding for the challenges of the energy transition.

The results of the three-year research project will be crucial for the transfer of the energy flexible industry into other regions in Germany. The experiences and findings within the Augsburg region will be a first prototype and an important step for the success of the energy transition in Germany and Europe.

Acknowledgements

The authors of this paper would like to thank the German Federal Ministry for Education and Research (BMBF) and the PTJ Project Management Agency for the sponsoring.

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IV Results and Future Research

In this section, the key findings of the doctoral thesis (Section IV.1) and the potential for future research (Section IV.2) are presented.

IV.1 Results

The main objective of this doctoral thesis is to contribute to investment risk and return management in digitized value networks and related energy flexibility management by supporting the design of future *decision support systems* (DSSs) that follow principles of *value-based management* (VBM). After introducing the transformation of traditional production systems to *cyber-physical production systems* (CPPSs) and digitized value networks, energy flexibility management is motivated by means of *demand response* (DR) in the light of challenges for industrial companies due to global energy transition. Furthermore, this doctoral thesis presents an integrated risk and return management cycle (cf. Hertel 2015) and motivates the design and development of new DSSs that assist companies in investment risk and return management. Subsequently, this doctoral thesis presents seven research papers that contribute to the development of such DSSs considering specific decision-making situations. In the following, the key findings of these research papers are presented. At the end, future research opportunities are discussed and a short conclusion is provided.

IV.1.1 Results of Section II: Decision Support for Risk and Return Management in Digitized Value Networks

Section II contributes to the design of future DSSs for investment risk and return management in digitized value networks. Section II.1 enables the development of future CPPS modeling approaches by providing a terminology, taxonomy, and reference model for CPPS entities, which is also a contribution to investment risk and return identification. Furthermore, Section II.2 helps companies to lower their costs for services on *infrastructure-as-a-service* (IaaS) spot markets by presenting a real options approach that evaluates and exploits temporal consumption flexibility. Section II.2 therefore contributes to investment risk and return quantification and control. Finally, Section II.3 contributes to the improvement of companies' systemic risk management by introducing a functional design and generic system architecture for respective DSSs. Thereby, Section II.3 especially emphasizes the need for (i) a value network-wide information management to gather and share risk-relevant information and (ii) future research, which should address highly relevant research questions. Therefore, Section II.3 contributes to investment risk and return management in an overarching manner.

- In Section II.1, Research Paper (RP) 1 addresses the missing common understanding regarding fundamental CPPS entities, which is required to develop urgently needed CPPS modeling approaches for efficiently designing and overcoming complexity and opacity in CPPSs. More precisely, the paper reviews current CPPS literature and summarizes that researchers apply varying numbers of different terms for CPPS entities and characteristics with varying levels of abstraction and granularity. To enable the development of future CPPS modeling approaches (Objective II.1), RP 1 makes the following contributions: RP 1 presents a terminology to standardize terms for CPPS entities, a taxonomy to classify CPPS entities within an is-a-relationship, and a reference model to illustrate abstract relations (associations and aggregations) between CPPS entities. Artifact development follows the iterative development process of Nickerson et al. (2013). Thereby, several loops of literature reviews, focus group discussions with other researchers, interviews with experts from industry, and internal discussions were conducted to simultaneously develop and evaluate the terminology, taxonomy, and reference model. Furthermore, RP 1 demonstrates the reference model's efficacy and general applicability by presenting three fictional and one real-world example. Thereby, despite its high degree of abstraction, the reference model proves to be suited for modeling different kinds of CPPSs with varying levels of distributed intelligence. This is especially confirmed by practitioners from expert interviews and researchers from focus group discussions. Moreover, these practitioners and researchers confirm that the terminology, taxonomy, and reference model contribute to a common understanding of CPPS entities and the reference model severs as a profound scheme to enable the development of more detailed CPPS modeling approaches in future.
- In Section II.2, RP 2 addresses companies' growing interest to externally source cloud computing services such as IaaS (Gartner 2017b). Thereby, IaaS spot markets exhibit volatile price developments, though prices are typically cheaper than for fixed price on-demand instances (Kamiński and Szufel 2015). Focusing on IaaS requests that possess temporal flexibility in execution, but, once started, must not be interrupted, RP 2 follows the objective to reduce companies' costs for such IaaS services

(Objective II.2) by presenting a real options approach for evaluating and exploiting temporal consumption flexibility considering cloud customers' individual deadlines. For *real options analysis* (ROA), RP 2 modifies, applies, and compares multiple discrete-time approaches based on Cox et al. (1979) and Tian (1993). For evaluation, simulations were conducted using historical data from an EC2 spot instance to analyze how well each approach would have provided decision support to exploit existing savings potentials due to temporal flexibility. Thereby, RP 2 provides novel real option approaches that explicitly forecast typical intraday patterns in spot market price development and demonstrates that these approaches improve quality of decision support compared to both traditional ROA without respective extensions and simple expectation optimization. Evaluation results indicate that, besides a small proportion of misjudgments, these novel real option approaches would have been able to exploit existing savings potentials to about 40 percent on average. However, return volatility on the analyzed EC2 spot instance and therefore savings potentials prove to be rather low. In this context, RP 2 elaborates arguments for why already minor relative savings for companies could nevertheless yield significant absolute savings and for why volatility on IaaS spot markets is likely to increase in future. Moreover, RP 2 elaborates reasons why cloud providers could also benefit from cloud customers that utilize their temporal flexibility, e.g., by applying suggested real option approaches.

- In Section II.3, RP 3 addresses the increasing problem of (structural) complexity and interdependencies in digitized value networks. Thereby, so-called systemic risks can cause huge supply chain disruptions (Scheibe and Blackhurst 2018), not only due to material dependencies but also due to informational dependencies (Akinrolabu et al. 2018; Chhetri et al. 2018). Therefore, RP 3 presents a functional design and generic system architecture for DSSs that help companies to improve (systemic) risk management (Objective II.3). The functional design for these so-called *risk management support systems* illustrates that such *information and communication technology* (ICT) must not only observe a company's business operations internally (i.e., within company borders) but also externally by additionally gathering and sharing information about and with related supply chain participants and (digital) service providers. By presenting the generic system architecture, RP 3 describes important components for such DSSs (i) to gather, filter, structure, and store both internal and external (risk-relevant) information and (ii) to process this information with the objective to qualitatively and quantitatively assess (systemic) risks and generate decision support. Hence, RP 3 contributes to existing literature by presenting the generic system architecture as a guiding concept for researchers and IS designers that strive to further develop and implement DSSs for (systemic) risk management. Moreover, the paper elaborates highly relevant challenges and research questions, researchers and IS designers need to cope with when further developing the generic system architecture into detailed designs for concrete application scenarios.

IV.1.2 Results of Section III: Decision Support for Risk Management in Energy Flexibility Management

Section III contributes to the design of future DSSs for investment risk and return management in energy flexibility management. With the objective to reduce a company’s electricity costs while improving utilization of renewable energy sources, Section III presents two real options approaches for evaluating and exploiting temporal flexibility in sourcing of electricity from real-time spot markets in general (Section III.1) and for the special use case of building *air conditioning* (a/c) systems, which additionally exhibit decaying effects of electrical work (Section III.2). Both Section III.1 and Section III.2 therefore contribute to investment risk and return quantification and control. With the same objective, Section III.3 derives important functional requirements and a generic system architecture for DSSs that assist decision-makers in energy flexibility management. Thereby, Section III.3 contributes to investment risk and return management in an overarching manner. Finally, Section III.4 helps companies to utilize their energy flexibility potential by providing a transdisciplinary research approach considering technological, ecological, and social restrictions. As this enhances a purely economic analysis, Section III.4 contributes to investment risk and return identification.

- In Section III.1, RP 4 addresses the problem of increasingly volatile electricity prices due to global endeavors of many countries to transform their energy generation to renewable energy sources. To yield monetary savings and improve utilization of renewable energy sources, companies can exploit their temporal flexibility in externally sourcing electricity (Objective III.1). For evaluating and exploiting temporal flexibility, RP 4 presents a real options approach. More precisely, RP 4 modifies and applies discrete-time option pricing based on Cox et al. (1979). As purchase of electricity is assumed to be obligatory within the company’s temporal flexibility window, the paper evaluates temporal flexibility as an option to defer the purchase. In addition, to provide decision support for companies, the model recommends in each discrete time step either to immediately purchase electricity or to defer the purchase for (at least) one more time increment. For evaluation, simulations were conducted using historical data from the electricity exchange EPEX SPOT (which was simulated as a real-time market) to analyze how well the approach would have provided decision support to exploit savings potentials. Evaluation results indicate that, besides a small proportion of misjudgments, the real option approach would have been able to lower electricity costs by 13 percent on average. Thereby, electricity cost savings would have increased significantly for longer temporal flexibility windows. RP 4 concludes that deferring purchase on electricity spot markets (i.e., using temporal flexibility) bears savings potentials and that the presented real option approach is a suitable method to exploit these savings potentials. For an additional proof-of-concept, a second evaluation was conducted with real-time prices from an U.S. market, which yielded similar results.

- In Section III.2, RP 5 addresses (like RP 4) the problem of increasingly volatile electricity prices. However, in contrast to RP 4, RP 5 focusses on the special use case of energy flexible a/c systems, which are among the biggest electricity consumers in the United States (U.S. Energy Information Administration 2018). A/c systems are used to change temperature inside a room or building (in terms of heating or cooling). Due to electricity spot markets' volatile price development, decision-makers should consider starting the building's a/c system already before actual occasions, e.g., the beginning of a shift in a production facility or occupancy of meeting rooms. However, within the building, there is thermal movement as the inside temperature continuously strives to converge toward outside temperature. Hence, a/c systems' electrical work is decaying over time and decision-makers should consider the tradeoff between volatile electricity prices and increasing electricity demand for early a/c activation. In this context, RP 5 presents an approach to minimize expected electricity costs by evaluating and exploiting short-term temporal flexibility (Objective III.2). Decision support is generated based on a short-term prognosis for both spot market price development and a/c electricity demand. While the former uses a modified version of the discrete-time price prediction model of RP 4, which builds upon typical intraday price patterns that can be observed in historical data, the latter is derived from a regression of historical a/c electricity demand on respective outside temperature development. Thereby, weather forecasts can be used by decision-makers to estimate future a/c electricity demand. For evaluation, simulations were conducted using historical data from two public buildings in the US (data: inside temperature, outside temperature, and a/c electricity consumption) and the local utility company (data: electricity prices). To date, a/c systems in these two buildings are activated continuously throughout the day and therefore waste a huge amount of electricity. Evaluation results indicate that, compared to the default procedure for a/c (*always on*), RP 5's approach would have reduced electricity costs by 45 percent on average. A second evaluation was conducted with electricity prices from the European market EPEX SPOT, which yielded similar results. Thereby, electricity cost savings would have increased significantly for longer temporal flexibility windows and for specific times of day (due to intraday patterns of electricity prices). However, since RP 5's evaluation applied hourly time increments to decide on initializing a/c, early a/c activation (i.e., at least one hour before room occupancy) was ex-ante optimal in less than one third of all simulations. This means that continuous thermal movement yields significant losses of the a/c system's electrical work. RP 5 concludes that utilizing an a/c system's temporal flexibility, i.e., flexibly activate a/c between two room occupancies, bears savings potentials compared to the default procedure and that the presented approach is a suitable method to exploit these savings potentials to a considerable extent.

- In Section III.3, RP 6 presents a generic system architecture for DSSs that identify, evaluate, control, and monitor industrial energy flexibility with the objective to lower a company's electricity costs (Objective III.3). Therefore, RP 6 derives important functional requirements for such DSSs, e.g., the necessity to integrate interfaces to energy markets and energy producing and consuming technologies inside the production environment. More precisely, RP 6 suggests that DSSs for industrial energy flexibility management should integrate all possibilities to conduct DR (energy flexible production processes, battery storages, *power-to-x* (P2X) technologies, and energy generation systems). The generic system architecture is based on the generic observer/controller architecture from the IS research domain of organic computing (Richter et al. 2006). It describes, first, the capability of such DSSs to observe a company's ICT for (i) procurement and sale on energy and balancing markets and (ii) deployment planning of production, energy storages, P2X, and power generation.

Second, it describes the capability of such DSSs to store, process, and analyze this information to determine current and future energy flexibility potential. Third, it describes the capability of such systems to provide decision support for optimally exploiting energy flexibility potential by analyzing various options for action based on machine learning, human objectives, and human frame conditions. As both the functional requirements and generic system architecture were evaluated and improved with three interviewed experts from practice, the artifact is designed to address a real-world business problem. To sum up, RP 6 contributes to existing literature by presenting a generic system architecture, which is a guiding concept of components with functions and information flows that helps researchers and IS designers to develop and implement DSSs in industrial energy flexibility management. Moreover, the paper contributes by elaborating recommendations for companies that are inexperienced with the development of complex DSSs and the topic of energy flexibility management.

- To save electricity costs by utilizing energy flexibility with respect to technological, ecological, and social restrictions that emerge beyond economic feasibility, RP 7 in Section III.4 presents a transdisciplinary research approach (Objective III.4). Therefore, RP 7 puts energy flexible factories in a broader context as they are emphasized to be important parts of the energy transition to renewable energy sources. To identify these restrictions and analyze possible problem areas that emerge from a regional integration of energy flexible manufacturing, RP 7 suggests collaboration of stakeholders from different disciplines and backgrounds such as scientists, plant operators, plant employees, and conservationists. Therefore, authors of RP 7 participate in a huge research project named *SynErgie*, which is funded by the German Federal Ministry of Education and Research (BMBF). Thereby, they particularly participate in a subproject named *energy flexible model region Augsburg* to research and apply new forms of collaboration between society and the energy flexible factories. In this transdisciplinary research approach, three phases are suggested: The establishment of a mutually shared understanding of different problem spheres (*co-design*), the development of valuable solutions (*co-production*), and the discussion of these solutions in interdisciplinary meetings with the objective to complement technical energy flexibility potential with socio-ecological guidelines that are practicable and commonly accepted (*co-communication and transdisciplinary re-*

integration). Furthermore, within the phase of co-communication and transdisciplinary re-integration, there is the objective to transfer the gained knowledge and experiences to a national level. As the research project is still running, RP 7 evaluates its current progress in three dimensions (cognitive-epistemic, social and organizational, and communicative) and concludes that knowledge integration of interdisciplinary stakeholders turned out to be the biggest challenge so far. To sum up, RP 7 contributes to literature and practice by presenting a transdisciplinary research approach that helps researchers and practitioners to utilize industrial energy flexibility without violating technological, ecological, and social restrictions imposed by (regional) stakeholders. Moreover, the identification and analysis of these restrictions contribute to investment risk and return management, as especially accompanying investment risks might otherwise be missed by decision-makers.

IV.2 Future Research

In the following, potential aspects for future research are highlighted for each section of this doctoral thesis.

IV.2.1 Future Research in Section II: Decision Support for Risk and Return Management in Digitized Value Networks

The limitations of RP 1 that provide opportunities for future research are:

- Artifact development in RP 1 was conducted following the iterative artifact development process of Nickerson et al. (2013) with several loops of literature reviews, focus group discussions, expert interviews, and internal discussions. However, by modeling on a high degree of abstraction, RP 1 refrains from modeling deeper technological details. This may raise difficulties for practitioners, as they must abstract their CPPS entities to the second lane of the proposed taxonomy. Therefore, future research should further develop the provided terminology, taxonomy, and reference model to integrate more technological details such as sub-entities of machines components (e.g., production machines, auxiliary machines, cross-sectional technologies, and storage systems).
- Furthermore, RP 1's contribution to a common understanding is limited to CPPS entities, although the paper additionally elaborates literature's missing clarity

regarding definitions and classification of CPPS characteristics and relations between these characteristics. Thereby, future research should grasp RP 1's research method and apply similar analysis to CPPS characteristics. The resulting artifacts could then be connected with the taxonomy and reference model for CPPS entities.

- Although RP 1's artifacts support the development of CPPS modeling approaches, there are further challenges for IS designers that are not addressed in this paper. For example, the instantiation of the reference model in huge production facilities could end up in complex *unified modeling language* (UML) class diagrams with numerous relations between CPPS entities, which would fail the objective to overcome complexity and opacity in CPPSs. Therefore, future research should think of complexity reducing representations of CPPS entities and their relations. Another drawback is the missing integration capability of the suggested reference model into other (existing) modeling approaches such as Plant Simulation (Siemens 2018) or Simio (Simo 2018). Therefore, researchers and practitioners should consider designing functional and technological interfaces to these software solutions and analyze how these solutions could be extended in light of RP 1's results.
- This doctoral thesis motivates RP 1 to support investment risk and return identification by reducing complexity and opacity in CPPSs and digitized value networks. However, as the paper provides its artifacts only from an information-driven perspective (i.e., all CPPS entities are either information receiver or transmitter or both), one major aspect is missing: Future research should integrate additional entities of pure physical value creation (e.g., auxiliary material and non-intelligent product components) to obtain a holistic representation of digitized value networks. This holistic representation is necessary to widen capabilities of investment risk and return identification, e.g., by simulating a system's robustness (in terms of losses of value creation) within different failure scenarios of integrated flows of information and material.

The limitations of RP 2 that provide opportunities for future research are:

- RP 2 limits its analysis of historical data (as input for artifact evaluation) to one specific EC2 spot instance. As other EC2 spot instances exist that feature higher return volatilities (Ekwe-Ekwe and Barker 2018) and therefore higher savings potentials than the one referred to in RP 2, future research should analyze and compare different EC2 spot instances to identify promising application scenarios for the presented real option approaches.

- RP 2 modifies, applies, and compares multiple discrete-time approaches based on Cox et al. (1979) and Tian (1993). Thereby, both original models demand a normal distribution of returns, which does not necessarily hold true for EC2 spot prices (Mazzucco and Dumas 2011). Therefore, future research should think of model extensions, e.g., by incorporating extreme value distributions in option pricing formulae.
- For reasons of simplicity, RP 2 restricts its ROA to discrete-time models, although analytical approximations or numerical solutions for continuous-time models would offer more flexibility of action for decision-making in terms of option exertion. Therefore, future research should consider the development of continuous-time model extensions.
- Furthermore, as RP 2's ROA is limited to the evaluation and exploitation of cloud customers' temporal flexibility, future research should also consider cloud customers' spatial flexibility. More precisely, prices on IaaS spot markets still lack liquidity and are subject to influencing factors such as home bias, wherefore they are not necessarily arbitrage-free between different providers and regions (Cheng et al. 2016; Fridgen et al. 2017). Moreover, future research could integrate analysis and optimization of both temporal and spatial flexibility.

There are several challenges and research questions that RP 3 elaborates within a research agenda as an orientation for interdisciplinary researchers and practitioners, who strive to further develop and implement DSSs for systemic risk management:

- The suggested DSSs require a technological interface for gathering and sharing information about and with related supply chain participants and (digital) service providers. Therefore, future research should compare and develop possible technological interface solutions such as centralized shared digital data bases, inter-organizational information systems for vendor-managed inventory and collaborative planning, forecasting, and replenishment systems, decentralized (product-centric) approaches such as the EPCglobal network (Muñoz-Gea et al. 2010), and technologies for secure multiparty computation following principles of Goldreich et al. (1987).

- Furthermore, future research should design technological interfaces for risk management support systems in a way that they limit concerns regarding security of information, privacy of information, and loss of intellectual property. In addition, incentives for sharing risk-relevant information should be researched.
- Considering management of the systemic risk-relevant information, future research should compare and develop different options for database systems such as data stream management systems, real-time database systems, and in-memory databases and different options for data processing technologies such as online transaction processing and online analytical processing.
- Moreover, future research should compare and develop different possibilities for risk management support systems to model and evaluate risks. Exemplary risk modeling languages are value-focused process engineering (Neiger et al. 2009), integrated modeling approaches (Arisha and Mahfouz 2010), modular Petri Nets (Fridgen et al. 2015), traditional graph theory (Wagner and Neshat 2010), and random graphs (Buldyrev et al. 2010). Exemplary risk evaluation measures are centrality measures, value at risk, and expected shortfall. In addition, future research should deal with the issue of modeling and evaluating risks with missing, incomplete, or inaccurate information.
- To continuously improve risk management support systems' decision quality, such DSSs should further integrate concepts from the IS research field of machine learning. Therefore, future research should compare and develop different machine learning techniques such as artificial neural networks, support vector machines, and random forest regression.
- Besides these open research questions that primary address the objective to compare and develop different technologies and measures, an important next step toward the realization of risk management support systems is to discuss the presented functional design and generic system architecture with practitioners in terms of possible applications and use cases.

Taken together, these potential research opportunities provide various starting points for future research toward the design and development of new DSSs for investment risk and return management in digitized value networks.

IV.2.2 Future Research in Section III: Decision Support for Risk Management in Energy Flexibility Management

The limitations of RP 4 that provide opportunities for future research are:

- The ROA presented in RP 4 is designed for real-time electricity spot markets that only feature immediate purchase of electricity according to currently valid price levels. However, some electricity spot markets such as EPEX SPOT feature so-called hour-ahead markets on which customers can purchase electricity not only in real-time but also several hours in advance. Thereby, price levels for a specific (delivery) hour can develop stochastically over time. Hence, modeling a dynamic hour-ahead market on which a decision-maker can decide between multiple real options for every hour of the day should be a feasible model extension, which may further increase a customer's savings potential due to temporal flexibility.
- RP 4 modifies and applies discrete-time ROA based on Cox et al. (1979). Thereby, the original model demands a normal distribution of the underlying's return (which is, in this case, the development of real-time electricity prices on spot markets). However, as returns of electricity spot prices usually feature tails that are rather heavy compared to normal distributions (Weron 2009), future research should think of model extensions, e.g., by incorporating extreme value distributions in option pricing formulae.
- Furthermore, as the presented ROA builds on a discretized version of a geometric Brownian motion, which is a stochastic process for modeling only positive values, the real options approach presented in RP 4 cannot account for negative spot prices, which already occur today and presumably more often in future at some electricity spot markets such as EPEX SPOT (Brijs et al. 2015). Therefore, future research should think of model extensions that explicitly allow for negative spot prices, e.g., based on a common Brownian motion.
- For reasons of simplicity, RP 4 restricts its ROA to discrete-time models, although analytical approximations or numerical solutions for continuous-time models would offer more flexibility of action for decision-making in terms of option exertion. Therefore, future research should think of continuous-time model extensions.

The limitations of RP 5 that provide opportunities for future research are:

- RP 5 focusses on one procedure for a/c in advance to room or building occupancy: After one-time activation, a/c is performed continuously until occupancy and not allowed to interrupt. Thereby, the presented DR approach cannot account for scenarios in which a decision-maker dynamically activates and deactivates the a/c system. Such a procedure should be developed by future research as it further increases managerial flexibility of action and therefore probably savings potentials.
- RP 5 focusses on temporal flexibility of a/c systems and therefore neglects further savings potentials by considering flexibility in quality (i.e., flexibility in targeted inside temperatures). Future research should develop a respective cost minimization approach or even integrate analysis and optimization of both temporal and temperature flexibility.
- RP 5 assumes that actual outside temperature equals previous temperature forecasts, i.e., there is no uncertainty in electricity demand forecasts. Indeed, weather forecasts for only a few hours are close to reality (National Weather Service 2017), which is confirmed by RP 5 as the paper (to mitigate this simplification) applies an additional sensitivity analysis, which implements an artificial hourly demand prediction error that proves to have only little influences on results. However, future research should further develop the presented approach and waive this simplification.
- Due to limited data availability, RP 5's evaluation cannot precisely predict electricity demand for initial a/c activation (which exhibits a certain payback load due to previous a/c deactivation and striving room temperature). The paper therefore only applies an interim solution. Thus, future research should analyze how buildings with certain properties (e.g., insulation, size, orientation) are exposed to thermal movement and therefore losses of previous electrical work of a/c systems and then extend RP 5's approach accordingly.
- Besides presented approaches for electricity price and demand prediction, future research could apply and compare other common modeling approaches such as Holt-Winters seasonal models (Holt 1957; Winters 1960) for electricity price prediction or consumption-based asset pricing models (Breeden 1979) for electricity demand prediction.

The limitations of RP 6 that provide opportunities for future research are:

- RP 6's functional requirements and generic system architecture for DSSs in energy flexibility management do not consider energy flexibility's temporal dimension. More precisely, it is not specified whether energy flexibility is analyzed in the short-term (e.g., process interruption in current production) or in the long-term (e.g., seasonal pre- and post-production). However, as relevant input parameters, human objectives, human frame conditions, or recommendations for actions depend on the temporal dimension, future research should incorporate this aspect when the generic system architecture is further specified.
- Furthermore, future research should specify concrete application scenarios for such DSSs as it is unlikely that every company that exploits its energy flexibility potential is required to implement all suggested system functionalities, which is especially necessary considering limited investment budgets and economic efficiency. Therefore, the development of a framework that matches companies' individual requirements with possible functionalities of the suggested DSSs could be helpful to determine economically feasible applications.
- Future research should further analyze, which kind of decision-making is suited for automatic control by the DSSs and which kind of decision-making is suited to stay under full human control. For example, while many companies would not mind relinquishing control over a production facility's a/c to autonomous control systems (if manual interventions are still possible), they would rather abstain from relinquishing control over their major production machines as any malfunction of the decision support software could result in huge economic damages to the company.
- As a general point: Since the generic system architecture is still on a high level of abstraction, each suggested component and flow of information should be further specified by researchers and practitioners to forward the realization of practical implementations of respective DSSs for energy flexibility management.

As the research project *SynErgie* and its subproject *energy flexible model region Augsburg* are still running, there are several open research questions from RP 7 that should be addressed either within this project or by future research. Some examples are:

- There is the need to analyze if different stakeholder groups consider energy flexible factories as one important part of the energy transition to renewable energy sources and if they are therefore willing to contribute to their realization and utilization. For example, they can contribute by paying higher retail electricity prices to enable incentives for companies to assist grid balancing or by accepting flexible shift work for employees in case that energy flexibility measures delay production schedules.

- Reversely, there is the need to research benefits that energy flexible factories generate for different stakeholder groups. For example, benefits could be (i) increased job security for employees due to companies' lower electricity costs and increased revenues for grid balancing, (ii) reduced levies for retail customers as necessary grid expansions may be reduced due to improved local grid balancing, or (iii) reduced greenhouse gas emissions as energy flexible factories can align their production with the availability of solar and wind power.
- As the project supports regional energy transitions, regional business models for utilizing energy flexible factories should be developed, which do not exist yet.
- To date, the research project still focusses on major industrial energy consumers as energy flexibility providers, which possess huge energy flexibility potentials within only a few production processes. However, future research within or outside this research project should also consider smaller energy consumers as flexibility providers, which can still contribute to this project's objectives as they exist in greater numbers. These smaller energy consumers may exhibit different challenges and requirements for offering energy flexibility, which should be researched and considered when designing appropriate business models.

Taken together, these potential research opportunities provide various starting points for future research toward the design and development of new DSSs for investment risk and return management in manufacturing company's energy flexibility management.

IV.3 Conclusion

Summarizing the research papers presented in Section II and III, this doctoral thesis contributes to the fields of investment risk and return management in digitized value networks and related energy flexibility management. The presented research papers especially investigate fundamental aspects that contribute to the design and development of future DSSs, which follow principles of VBM by emphasizing an integrated risk and return identification, quantification, control, and monitoring. As an integrated risk and return management will continue to play an important role for manufacturing companies in times of digitalization and global energy transition, this doctoral thesis provides valuable supportive approaches.

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